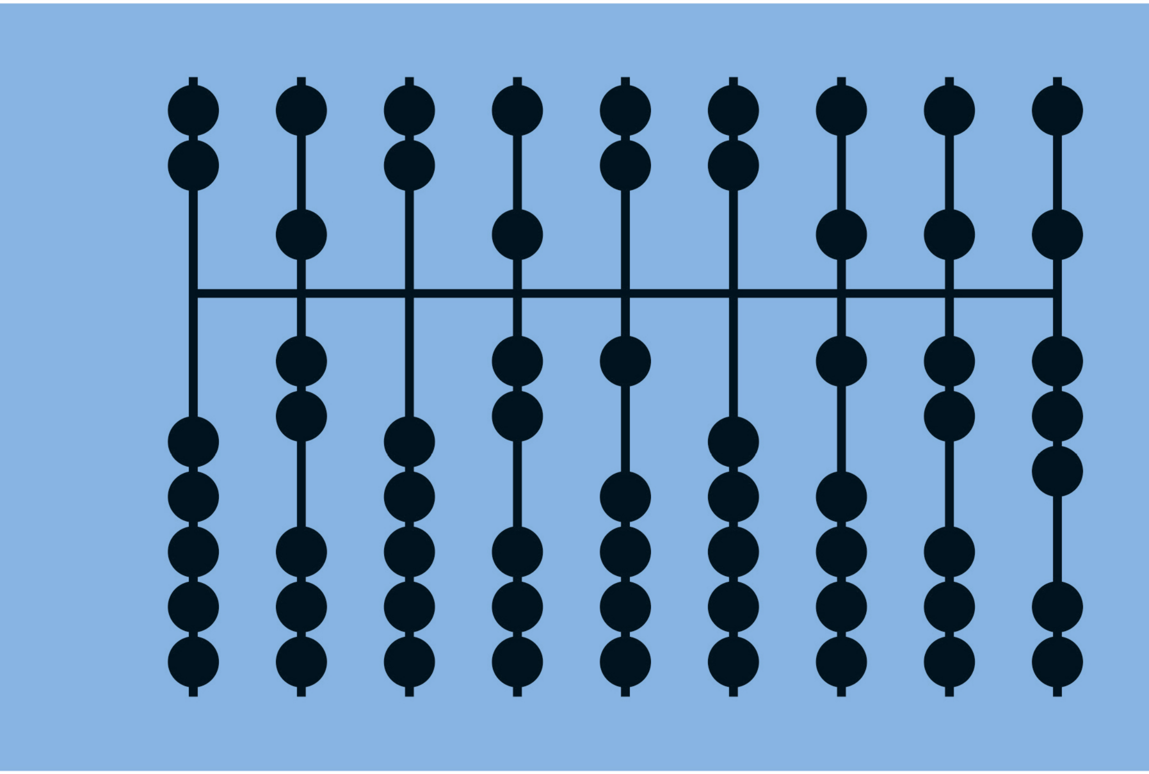
RUTGERS STUDIES IN ACCOUNTING ANALYTICS

Audit Analytics in the Financial Industry



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Introduction: What is Audit Analytics?

Jun Dai and Miklos Vasarhelyi

The spate of accounting scandals and corporate failures since 2001 has brought unprecedented attention to the importance of corporate governance. The Enron scandal, revealed in October 2001, resulted in a loss of about $80 billion in market capitalization for investors (The Washington Post, 2002), and a year later, an audit team unearthed $3.8 billion in fraud at WorldCom (Pulliam & Solomon, 2002). Since then, both professional auditors and audit researchers have devoted significant effort to improving the capabilities of auditing, internal control, and continuous monitoring (Alles, Brennan, Kogan, & Vasarhelyi, 2006; Byrnes, 2015; Chan & Vasarhelyi, 2011; Jans, Alles, & Vasarhelyi, 2014; Vasarhelyi, Alles, & Williams, 2010).

"Big data" is receiving increased attention from accounting practitioners. Organizations have collected more data in 2 years than in the previous 2,000 years (Syed, Gillela, & Venugopal, 2013). For example, Walmart collects more than 1 million customer transactions every hour, and Facebook collects more than 200 gigabytes of data per night (Cao, Chychyla, & Stewart, 2015). In addition to data stored in traditional accounting systems, auditors are also able to acquire evidence from vast amounts of other complex data, such as non-financial data extracted from modern enterprise resource planning (ERP) systems or online databases, radio frequency identification trackers and networked sensors, social media, and even closed-circuit television videos in stores (Moffitt & Vasarhelyi, 2013). In addition, many countries now permit some of their government administrative information and data collected from their citizens and businesses to be open to the public, which provides auditors with even more data for monitoring and investigations (Dai & Li, 2016; O'Leary 2015; Schneider, Dai, Janvrin, Ajayi, & Raschke, 2015).

To extract and process data from a variety of sources to be used for identifying risks, collecting evidence, and ultimately supporting decisions, auditors are utilizing the emerging technology of audit analytics (AA). AA is defined as a science of

> discovering and analyzing patterns, identifying anomalies, and extracting other useful information in data underlying or related to the subject matter of an audit through analysis, modeling, and visualization for the purpose of planning or performing the audit. (AICPA, 2015)

The predecessor of AA is the analytical procedure, which has long been used as one of external auditors' techniques in the planning, substantive testing, and completion phases of audits (AICPA, 2015). Since analytical procedures performed in the planning phase typically "use data aggregated at a high level" (AICPA, 2012), "the results of those analytical procedures provide only a broad initial indication about whether a material misstatement may exist" (AICPA, 2012). AA techniques can be applied to transaction-level data because such techniques generally maintain good performance even when used on huge and high-dimensionality data sets. As a result, AA can enhance the accuracy of risk assessment and improve the quality of planning.

Traditional analytical procedures usually rely heavily on sampling of audit-related data (AICPA, 2015). However, as large-scale ERP systems are rapidly growing in popularity among businesses, sufficient evidence can no longer be collected from only a sample of data. AA increases the tested population from limited samples (judgmental or statistical) to millions of transactions in full population testing, which enlarges the audit coverage from a small percent of overall transactions to the entire population (AICPA, 2015). Besides data recorded by a client firm's ERP system, auditors also have access to public data, such as social media postings (Moon, 2016), open government data (Dai & Li, 2016; Kozlowski, 2016), and weather data (Yoon, 2016). Emerging data analytics technologies have the capability to explore vast amounts of data in various structures and formats, which cannot be handled by traditional analytical procedures.

AA offers several advantages over traditional approaches. First, audit data analytics are more cost-effective in terms of evidence collection. On average, AA costs $0.01 compared to $4 for a standard audit of the same evidence.[1] In addition, many data analytics techniques are scalable in that they can generally maintain good performance when handling huge and high-dimensionality datasets (Alpaydin, 2010). Some AA techniques also have the ability to identify data patterns in an unsupervised learning paradigm in which the training data sets for building detection models do not need to contain class label information (Byrnes, 2015; Thiprungsri & Vasarhelyi, 2011).

Part One of this book presents two articles illustrating the process of applying AA to solving audit problems. Part Two contains four studies that use various AA techniques to discover fraud risks and potential frauds in the credit card sector. Part Three focuses on the insurance sector and uses two articles to show the application of clustering techniques in auditing. Part Four includes two chapters on how to employ AA in the transitory system for fraud/anomaly detection. Parts Five and Six illustrate the use of AA to assess risks in the lawsuit and payment processes.

Auditing researchers have been devoting significant efforts to integrating AA techniques into existing audit programs. AA can facilitate various stages of the audit process with simple or complex tests. Chapter 1 summarizes exploratory data analysis (EDA) techniques and the audit stages in which they could be employed for both internal and external audits. This research also conceptualizes the process of implementing EDA in audit procedures. Similarly, Chapter

[1]http://raw.rutgers.edu/node/89.html

2 provides guidance for auditors to apply these new technologies in actual audit work.

A variety of AA technologies can be employed to facilitate risk discovery, anomaly identification, and fraud detection. Chapters 3–5 explore the use of clustering methodologies to identify risky customer groups for a bank's credit card department. After grouping customers with similar characteristics and purchase/payment behaviors into clusters, the bank can manage each group differently and take actions for high-risk credit card holders.

Similar approaches are also employed to identify abnormal life insurance claims. Chapter 7 uses a simple *K*-means clustering model to group claims with similar characteristics and to flag unusually small clusters for further investigation. Chapter 8 explores the attributes to be used to identify outliers, and then uses clustering to assess whether life/disability insurance claim settlements are reasonable and whether the claims themselves are legitimate.

Decision tree is an AA technique that is easy to understand and can facilitate risk and error identification effectively by learning the characteristics and behavior patterns in the data. Chapter 6 shows the potential of Decision Trees for helping internal auditors to identify credit card delinquency, and Chapter 11 applies the Decision Tree methodology to the risk of lawsuits for credit card customers.

Fraud detection is another domain that can benefit from AA techniques. By analyzing transaction-level data, AA can capture unusual data flows and abnormal patterns. Chapters 9 and 10 illustrate how rule-based systems can facilitate fraud detection by incorporating expert knowledge into models. Chapter 9 illustrates the development and testing of a model to detect anomalous transactions in a bank's transitory accounts. Chapter 10 detects fraudulent transactions in the payment process for wire transfers by identifying potential fraud indicators, each of which is assigned a risk score based on perceived severity. Payments with total scores that exceed a threshold would be considered potentially fraudulent transactions that can be recommended for further investigation. Internal control is another important and complex area that could benefit from AA. In Chapter 12, two methods are presented. One of them is fuzzy logic which is used to create a generic risk model for assessing internal controls over payments and the other is the use of statistical tools to detect outliers and anomalies on the data.

The goal of this book is to provide insights for academics, auditors, and business professionals on potential applications of AA in the financial industry. Real-life data and audit problems are used to demonstrate how AA can facilitate the discovery of audit concerns that would be difficult or time consuming if traditional approaches were used.

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