A Study on the Analytical Procedures using Artificial Intelligence Methods

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ABSTRACT

In this study, we attempt to improve analytical methods in auditing by applying Artificial Intelligence(AI) methods including Artificial Neural Networks(ANN) and Case-Based Reasoning(CBR), and to perform pattern recognition of the investigation signals generated by analytical procedures. Five years of audited financial data from a large-sized firm were used to calculate four commonly applied financial ratios. This exploratory study shows that the use of AI methods to analyze patterns of related fluctuations across numerous financial ratios provides improved performance in recognizing material misstatements within the financial accounts.

1. Introduction

The audit process consists essentially of the collection and evaluation of evidential matter concerning financial statement items through the evaluating of the client's internal control system, and conducting substantive tests. The latter includes tests of details of transaction and balances, and *Analytical Procedures*(AP) of significant ratios and trends, resulting in investigating unusual fluctuations and questionable items.

AP based on annual financial statement account balances are used in the early stages of the audit process. AP involve a comparison of the client's reported balances with the auditor's expected or reasonable values of these balances, and aim at determining the extents to which reported items deviate from expectations. These AP play an important role in the preliminary audit process [4,6]. Additionally, *Statement on Auditing Standards No. 56- Analytical Procedures* require the use of AP in the planning and review stages of all audits. Our auditing standards also require the *Analytical Procedures* as one of general auditing procedures from 1991. They refer to general meaning and applicable timing of AP, but not refer concretely to usable methods of AP. Thus, the methods of AP have been determined by auditors' opinion. Recently, the need for knowledge and application about AP is rapidly expanding because of increasing pressures to minimize audit costs. Despite AP' importance and effectiveness, however, the knowledge and practical application about AP are quite sparse. It is due to the difficulty in predicting reasonable expected value and classifying pattern of trends.

Artificial Neural Networks, a type of artificial intelligence technology, are able to recognize patterns in data even when the data is noisy, ambiguous, distorted, or variable [2,4,7]. It is only a few years since ANN started to be applied to bankruptcy prediction, bond rating and the going-concern problem in business. ANN have outperformed standard statistical methods when applied to examine actual financial data.

Case-Based Reasoning, another field of AI, is rapidly emerging as a rich, versatile and powerful AI approach capable of solving complex, expertise-driven problems. CBR is a form of approximate reasoning that relies on past cases to aid in driving solutions or decisions for current problems [1]. CBR as a close approximation for similar 'detection' tasks, such as monitoring for money-laundering payments in the banking system, picking tax returns that qualify for audits [8]. Therefore, CBR may be useful to recognize the patterns of investigation signals generated in AP.

In this study, in order to recognize pattern of financial ratios, statistical methods are applied to AP. In addition, Artificial Intelligent methods including Case-Based Reasoning and Artificial Neural Networks are applied to AP.

The remaining sections of the article is organized as follows. In section 2, the methods of AP employed in this study are reviewed. Simulation procedures for the experiments are presented in section 3. Results and conclusion are given in section 4.

2. Experimental Methods

2.1 Financial Ratio Procedure(FRP)

The financial ratio procedure for evaluating the effect of errors on financial ratios is based on a statistical rule proposed by Kinney [6]. The rule signals an investigation when the difference between book values for the test month and the expected audited value is so large in relation to past differences.

The decision rule is to investigate the accounts comprising the ratio if the calculated test statistic exceeds a preset critical value for the deviation. If the distribution of standardized changes is normal, a Z-value based on a risk level specified by the auditor may be used as the critical value. Thus, an investigation is indicated whenever the test statistic is greater than positive critical value or is less than negative critical value based on a risk level the auditor specifies.

2.2 Pattern Analysis Procedure(PAP)

The financial ratio procedure attempts to identify unusual fluctuations in the financial ratios and alert the auditor that additional investigations may be warranted. The pattern analysis procedure is a crude analysis for the monthly cross-sections of the financial ratios. The purpose of the pattern analysis procedure is to determine whether the signaled fluctuations within each the stream of ratios are consistent with the expected combination of fluctuations.

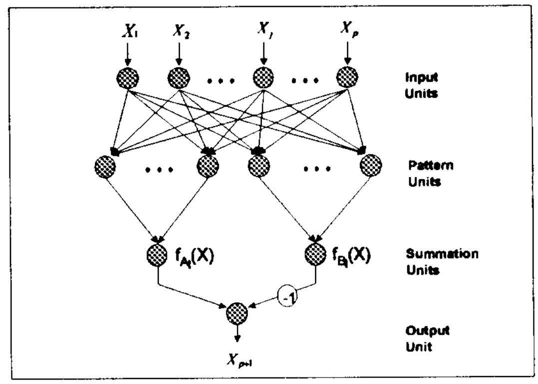
The model for evaluating the pattern analysis of the financial ratios is based on the Guidelines for Selection of AP presented by Coakely [4]. The combination of investigation signals from the financial ratios is compared with the expected combination of signals that would occur if error is present. The comparison is based on an analysis that predicts the direction of the change in the financial ratio if a monetary error from the specified financial transaction is present in the accounts. Financial ratios were used in this study to provide a benchmark for comparing ANN and CBR methods. Four ratios - Receivables Turnover, Inventory Turnover, Cost of sales Ratio, Accruals Ratio - were calculated for the five audit periods using ending balances. These ratios (or variants) have previously been evaluated to determine their effectiveness as AP.

2.3 Artificial Neural Network Procedure

Since we have used sparse patterns (192 patterns) in this study, we employed Probabilistic Neural Network (PNN), a type of ANN, that offer much swifter response as alternative learning technique. The PNN provides a general technique for solving pattern classification. The PNN, in contrast to the BPN model, trains very quickly. Another strong point of the PNN is that the smoothing parameter, which affects the generality of decision boundaries, can be modified without retraining [9].

PNN is composed of three layer networks wherein the training patterns are presented to the input layer and the output layer has one neuron for each possible category. PNN separates data into a specified number of output categories. There must be as many neurons in the hidden layer as there are training patterns.

<Figure 1> shows the architecture of a PNN. The pattern units whose incoming weights correspond to the set of training vectors utilize an exponential function instead of the sigmoid function commonly used in BPN. The summation units which sums the Parzen Kernels for each class.



<Figure 1> An elementary probabilistic neural network (PNN).

The network produces activations in the output layer corresponding to the probability density function estimate for that category. The highest output represents the most probable category. Within this study, we have used Neuroshell 2 which is one of the commercial packages to create and apply a PNN. The network has four input elements, corresponding to the four calculated monthly financial ratios. The pattern units consists of 192 processing elements, corresponding to the 192 samples in the training set. Four output units were used: a separate output unit to signal the absence of material error, the presence of material error from each of two potential sources of error investigated in the study, and a fourth unit to signal the presence of material error from either or both sources. <Table1> shows the structure of the PNN employed in this study.

Number of input nodes	four types
Number of output nodes	four types
Number of hidden layers	one
Number of nodes in hidden layer	the number of patterns (192)
Transfer function	the exponentitation
Paradigm	Supervised multilayer

<Table 1> The structure of the PNN

2.4 Case Based Reasoning Procedure

When applying CBR method to the cases, selecting number of nearest neighbors is most important. This approach involves the assessment of similarity between stored cases and the new input case, based on matching a weighted sum of features. In this study, we employed _composite neighbor_ proposed by Kim, S. and Kang, D [5] since it could be suit for pattern classification. The key to the composite approach is to determine the most effective set of weights to use in order to construct the virtual neighbors .

<Figure 2> depicts CBR procedures used in this study. 144 patterns were used as the past cases. The remaining 48 patterns were as test set to measure the effectiveness of the CBR procedures.

0. Begin with current case x(t).
1. Seek the J neighboring cases $X(t_i)$ in the past which are closest to x(t) according to the distance

$$d_i = d[x(t_i), x(t)]$$

2. Compute the sum of weights:

$$d_{TOT} = \sum_{i=1}^{J} d_i$$

3. Determine the relative weight of i^{th} neighbor :

$$w_i = \frac{1}{J-1}[1 - \frac{d_i}{d_{TOT}}]$$

4. Find the successor $x(t_i+1)$ of each case $x(t_i)$ in the set of neighbors.
5. Calculate the forecast for t+1 as the weighted sum of

$$\hat{x}(t+1) = \sum_{i=1}^{J} w_i x(t_i + 1)$$

<Figure 2> Procedure through case reasoning composite neighbors

In the same way of the PNN procedures, four output units were used: a separate output unit to signal the absence of material error, the presence of material error from each of two potential sources of error investigated in the study, and a fourth unit to signal the presence of material error from either or both sources.

3. Simulation Procedures

In this study, selected attention-directing AP are applied to actual monthly account balances for a single large firm over the five auditing years (1991-1995). Actual month-end balances were obtained by a responsible person in charge of the accounts. The case firm has relatively good internal accounting controls and modified perpetual inventory system for inventory and cost of sales. Independent personnel make test counts of the inventory to estimate the total ending inventory. Each of the five year was audited but the monthly balances were not audited individually. It was assumed that these monthly balances were free of material errors.

3.1 Seeding of monetary errors

A simulation was performed to evaluate the effectiveness of the FRP, PAP, PNN pattern analysis, and CBR pattern analysis methods in signaling the absence and presence of material errors. The simulation process produces three distinct cases regarding the seeding of monetary errors into the financial accounts and aggregates:

- No material monetary errors are seeded. Since we have assumed that the reported balances are free of material errors, they can be used to evaluate the efficiency of the procedures. The procedures produce correct decisions if the procedures do not signal the need for additional investigations when monetary errors do not occur in the financial balances. When additional investigations are signaled in this case, they are assessed as Type I errors.
- In a similar manner, if the seeded monetary error was less than a material amount, an efficient AP would not signal further investigation. When additional investigations are signaled in this case, they are assessed as Type I errors, too.
- Material monetary errors are seeded. When material monetary errors are seeded into the accounts, a reliable AP should signal the need for further investigation. When additional investigations are not signaled in this case, they are assessed as Type II errors.

In the application of AP, the desired level of overall materiality (M), the α level for the confidence interval of the error, and the predicted value influence efficiency and reliability of AP. In this study, the amount defined 'material' is based on the functional relationship developed by Warren and Elliot [10]:

$$Materiality(M) = 0.038657 * (Revenues)^{0.867203} \quad (1)$$

Iceman and Hillison [3] compared material amounts derived from the formula in equation (1) with empirical data collected from 49 manufacturing firms. Their analysis reported that the formula produced values consistent with the size of individual errors that resulted in adjustments to the financial statements. According to their study, the formula in equation (1) can be used to provide a reasonable approximation for materiality.

3.2 Performance Measure

The combinations of outcomes and states of nature result in four types of attention-directing decisions as shown <Table 2>. Correct decisions result when the size of the monetary error is less than a material amount and an investigation is not signaled, and when the size of monetary error is greater than or equal to material amount and an investigation is signaled. The sum of Type I and Type II error rates was compared to a benchmark value of 1.0 as a measure of effectiveness.

Size of Error in Reported Balance	Results of AP	
	Investigation Signaled	Not Investigation Signaled
Less than Materiality	Type I error	Correct Decision
Greater than Eaqual to Materiality	Correct Decision	Type II error

<Table 2> Types of attention-directing decisions

This benchmark value is biased on the notion that if any random process is used to decide whether a material error exists in account balance, the sum of the resultant Type I and Type II error rates has an expected value of 1.0. A lower Type I error rate would indicate that a procedure is more efficient and a lower Type II error rate would indicate that a procedure is more reliable and a lower combination of Type I and Type II error rates would indicate that a procedure is more effective.

3.3 PNN and CBR training

The PNN and CBR pattern analysis procedures were trained using the evaluated financial ratios in the base period. The ratios were standardized and normalized from 0 to 1 and then provided as input to the PNN and CBR. In total, 192 patterns -a set of four ratios- were created. Because the PNN and CBR is to separate outputs into different categories, four outputs were required. The outputs were desired category set to 1, and all others to 0. Within this study, 144 patters were used for training set - especially for PNN procedure, test set, 20% within training set were randomly selected - and remaining 48 patterns for validation set were used to evaluate the performance of the PNN and CBR procedures.

4. Results and Conclusion

<Table 3> summarizes the error rates of the AP used in this study and presents that AI based procedures have much higher performance than the others. Based on the averaged error rates, the AI approaches are noticeably more effective, that is, the composite Type I and Type II error rates are lower.

	Presence of Error	Source of Error
FRP	0.764	N/A
PAP	0.596	0.929
CBR	0.271	0.469
PNN	0.291	0.499

<Table 3> Comparison of combined error rates

This study continued the development of a methodology that can be applied to analyze the complex patterns of related fluctuations across numerous financial accounts and identify the presence and plausible source of a material monetary error in the accounts. Results suggest that the use of AI methods as a supplement to traditional analytical procedures will offer improved performance in recognizing material misstatements within the financial accounts. This study was limited to the analysis of a single firm over a 48 month period under ideal conditions as a preliminary study on the use of AI methods.

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