CLUSTER ANALYSIS FOR ANOMALY DETECTION IN ACCOUNTING

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ABSTRACT

Cluster Analysis for Anomaly Detection in Accounting

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Cluster Analysis is a useful technique for grouping data points such that points within a single group or cluster are similar, while points in different groups are different. The objective of this study is to examine the possibility of using clustering technology for auditing. Automating fraud filtering can be of great value to continuous audits.

In the first paper, cluster analysis is used to group transactions from a transitory account of a large international bank. Transactions are clustered based on the open comments field. Major types of transactions are discovered. These results provide a new knowledge about the nature of transactions that flow into transitory accounts.

In the second paper, cluster analysis is applied to wire payments within an insurance company. Different anomaly detection techniques are examined. No wire transfer is flagged by all techniques. These results do not necessarily indicate that there is no real anomaly in the dataset, but that different assumptions, parameters or settings should be examined.

In the third paper, cluster analysis is applied to group life insurance claims. Individual claims which have significantly different characteristic from other members in the same cluster as well as clusters which comprise of less than 2% of the population are

identified as possible anomalies. Moreover, rule-based detection techniques are used to assist internal auditors in selecting claims for further investigation. Cluster analysis and rule-based detection can be combined for the efficiency and effectiveness of the implementation by internal auditors.

Cluster analysis has been used extensively in marketing as a way to understand market segments and customer behavior. This study examines the application of cluster analysis in the accounting domain. It can be used for exploratory data analysis (EDA), but also can be used for anomaly detection (i.e. for audit purposes). The results provide a guideline and evidence for the potential application of this technique in the field of audit.

DEDICATION

To My Parents, Nakorn and Rampai Thiprungsri

For their love and support throughout my life.

This dissertation would not exist without countless sacrifices they have made for me.

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Chapter 1 Introduction

1.1 Background

Clustering is an unsupervised learning algorithm, which means that there is no label (class) for the data (Kachigan, 1991). Clustering is a useful technique for grouping data points such that points within a single group or cluster are similar, while points in different groups are different. In general, the greater similarity within a group and the greater differences between groups mean the better clustering results. There is no absolute best clustering technique (Kachigan, 1991). User's needs are also an important factor in evaluating the clustering technique. The best techniques are those that could provide the results which are useful for the user's purposes. Moreover, cluster evaluation is quite subjective because the results could be interpreted in different ways. Several factors should be considered when deciding upon which type of clustering technique to use. These factors are, for example, type of clustering techniques, type of cluster, characteristic of clusters, characteristics of the dataset and attributes, noise and outlier, number of data objects, number of attributes, cluster description, and algorithm considerations (Tan et al, 2006).

Clustering as an unsupervised learning algorithm is a good candidate as a fraud and anomaly detection technique. It is difficult to identify suspicious transactions. Clustering can be used to group transactions so that different treatment and strategies can be applied to each different cluster. The purpose of this study is to examine the possibility of using clustering techniques for auditing. Cluster Analysis will be applied to three datasets. The first dataset encompasses transitory accounts from a bank. The second and

third datasets, a wire transfer and a group life insurance claim file, are from an insurance company.

In the first paper, cluster analysis has been used to group transactions from a transitory account of a bank. Transactions are grouped or clustered based on the open comment field. Seven clusters representing seven types of transactions are formed. In the second paper, cluster analysis has been applied to wire transfers within an insurance company. Four detection techniques are used to identify possible anomalies. In the third paper, cluster based outliers have been examined. Group life insurance claims have been grouped. Those clusters with small populations have been flagged for further investigation.

This dissertation is organized into six parts. The next section of the introduction gives a summary of fraud detection in accounting and the basic idea of cluster analysis. Then the literature review sections outline some methodological issues found in clustering analysis, the fraud detection using data mining techniques, continuous auditing, and research questions. The later parts of this dissertation comprise of three research studies done on three different dataset to demonstrate the possible usage of cluster analysis. The final chapter outlines the summary of findings, discusses the shortcomings of this approach, suggests continuation and further research in this area and draws conclusions for this dissertation.

1.2 Fraud

1.2.1 Type of Fraud

There are many definitions of fraud. Webster's New World Dictionary (1964) states:

> *Fraud is a generic term and embraces all the multifarious means which human ingenuity can devise, which are resorted to be one individual, to get an advantage over another by false representations. No definite and invariable rule can be laid down as a general proposition in defining fraud, as it includes surprise, trickery, cunning and unfair ways by which another is cheated. The only boundaries defining it are those which limit human knavery.*

Fraud always involves deception, confidence and trickery. Albrecht et al (2006) define that the most common way to classify fraud is to divide frauds into 1) those committed against an organization and 2) those committed on behalf of an organization.

For fraud committed against an organization, or occupational fraud, the employee's organization is the victim. This type of fraud can be anything from security break abuses to serious high-tech schemes. The Association of Certified Fraud Examiners defines this type of fraud as, "The use of one's occupation for personal enrichment through the deliberate misuse or misapplication of the employing organization's resources or assets" (Association of Certified Fraud Examiners, 1996).

The most common fraud committed on behalf of organization is fraudulent financial reporting. It is usually committed through actions of top management. These frauds are committed to make the companies' financial statements look better for various reasons such as to increase stock's price, to ensure a larger year-end bonus for executives, to get better financing terms and etc. Management fraud is distinguished from other types of fraud both by the nature of the perpetrators and by the method of deception (Albrecht et al, 2006).

Based on a series on interviews, Cressey (1953) introduces the fraud risk factor theory, called "fraud triangle". Cressey concludes that frauds generally share three common traits: pressure, opportunity, and rationalization. These three key traits can be used to identify factors that are always present in any given fraud. Whether the fraud is an employee fraud or management fraud, these three elements will always be present.

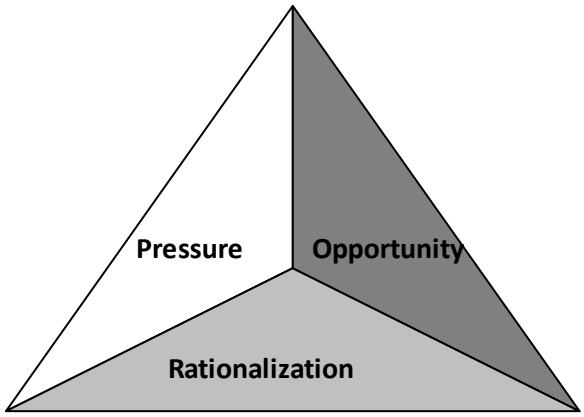

Figure 1.1 Fraud Triangle.

Albrecht et al (2006) explains the fraud triangle theory which will be summarized in this section. The first element is **pressure**. It is increased when financial stability or profitability is threatened by economic, industry, the firms operating conditions and / or the third parties. Management or other employees may have incentive or be under pressure, which provides a motivation to commit fraud. The second element is a perceived opportunity to commit fraud, to conceal it, or to avoid being punished. **Opportunity** is increased by factors such as industry characteristics, ineffective monitoring of management, insufficiency and or inefficiency of internal controls. Circumstances can exist, for example, the absence of controls, ineffectiveness of the existing controls and ability of management to override the controls, which provide the opportunities for fraud to occur. **Rationalization** is the attitudes or rationale by board

members, management and/or employee that allow them to committee fraud. Fraudsters need a way to rationalize their actions as acceptable. They tend to believe that their actions are for a good cause; hence, they are acceptable. Some individuals possess an attitude, set of ethical values, or character, that motivates/allows/facilitates/justifies them to knowingly and intentionally commit fraud.

The fraud triangle theory described above is widely accepted and adopted by the American Institute of CPA's (AICPA) in the Statement on Auditing Standards (SAS) No.99, "Consideration of Fraud in a Financial Statement Audit". SAS No. 99 states in paragraph .31 as following

> *Because fraud is usually concealed, material misstatements due to fraud are difficult to detect. Nevertheless, the auditor may identify events or conditions that indicate incentive/pressure to perpetrate fraud, opportunities to carry out fraud, or attitudes/rationalizations to justify a fraudulent action. Such events or conditions are referred to as "fraud risk factors". Fraud risk factors do not necessarily indicate the existence of fraud; however, they often are present in circumstances where fraud exists.*

SAS No. 99 also gives examples of fraud risk factors to guide practitioners. Not all of examples are relevant in all circumstances. Some may be at greater or lesser significances in entities of different size, with different organizational characteristics or circumstances.

Despite the popularity of the fraud triangle theory, little is known about the dynamic relationship among each aspect of the fraud triangle. Loebbecke et al (1989) find that when all three components are present concurrently, it is likely that management fraud exists. If only one component is present, there is lower likelihood of fraud. These findings do not help much in understanding the dynamic of the relationships.

Albrecht et al (2006) believes that the three elements are interactive. For example, the greater the perceived opportunity or the more intense the pressure, the less rationalization it takes to motivate someone to commit fraud. On the other hand, the more dishonest a perpetrator is, the less opportunity and/or pressure it takes to motivate fraud. There is little research evidence to back up the claim.

How do all aspects affect each other? A better understanding of the relationship among of three aspects, opportunity/condition, pressure/incentive, and rationalization/attitude, is needed.

The fraud triangle theory is well accepted and adopted in many disciplines. Albrecht et al (2004) combine the fraud triangle theory with agency theory from economic literature and stewardship theory from psychology literature. This is later known as "the Broken Trust" theory (named by Choo et al, 2007). The theory describes corporate management fraud using corporate executive behavior, compensation and corporate structures. . Choo et al (2007) extend the broken trust theory with the "American Dream" theory from sociology literature. Three high profile management fraud events in the United States (Enron, WorldCom, and Cendant) are used as anecdotal evidences to support the theory.

1.2.2 Error and Anomaly

According to American Heritage College dictionary (2004),

> *Error n. 1.An act, assertion, or belief that unintentionally deviates from what is correct, right or true. 2. The conditional of having incorrect or false knowledge. 3. The act of an instance of deviating from an accepted code of behavior. 4. A mistake.*
>
> *Anomaly n. 1.Deviation or departure from the usual or common order, form or rule. 2. One that is peculiar, irregular, abnormal, or difficult to classify.*

Based on fraud triangle theory, the distinguishing factor between fraud and error is the intention. Error is the deviation from the usual behavior. It does not have the element of intention to deviate. Therefore, a deviation or anomaly could be a result of an error or an intention to commit fraud.

Anomalies are generated from many reasons; for example, data may come from different classes, natural variation in the data and data measurement or collection error (Tan et al, 2006). The first reason, data coming from different classes, is probably the most important type of the anomaly. It is the focal point of anomaly detection in data mining. For examples, fraudulent transactions belong to a different class from normal transactions, i.e. fraudulent transactions are initiated by hackers. They usually are generated from different source, i.e. fraudulent customers. The data can also have natural variations. In other words, most data will be near the center (or the average); while the further away from the center, the lesser number of observations will be present. Errors and anomalies can also come from errors in measurement. The data may be incorrectly recorded because the equipment malfunctions and/or human error. For example, a weight scale always reads out 1 pound less than the real weight, a researcher reads out the temperature a few degrees higher than the real temperature because he/she misread the scale and etc. This type of data will provide no useful information. It should be cleaned in the preprocessing step (or data cleaning step).

1.3 Cluster Analysis

1.3.1 Basic concept

Cluster analysis groups the objects or databases only on information found in the data that describes the objects and their relationships (Tan et al, 2006). Each object is very close or similar to other objects in the same group (the closer, the better), but different from objects in the other groups, (the greater differences, the better). It begins with a single group, follows by attempt to form subgroups which are different on selected variables. To determine what variables to be used is not an easy task. Even if there is a clear answer to the preceding question, the following question will be how it should be measured. Clustering can be used for data exploration and also to understand the structure of data. Without the prior knowledge about the data, cluster analysis can be used to search for common characteristics of sub groups in the data.

The two major steps in cluster analysis are 1) selecting measures of similarities or dissimilarities, and 2) selecting the procedures for cluster formations (Kachigan, 1991). There are several options or techniques available for these steps, making cluster analysis as much as art as a science. It is not simple to choose and interpret the results. Moreover, while running simulations on cluster analysis, Milligan et al (1985) find that that performance of some cluster analysis procedures can also be data dependent. Generally the purpose of performing cluster analysis is to ask the question whether a given group can be partitioned into subgroups which have different characteristics. The subgroups or clusters can be named or defined using the common characteristics of the group members such as group mean for the numeric values as the representative of the observations in the group, or using the most common or majority values in the subgroups. For example, in

marketing, customer segments (or clusters) are defined using demographic information (Erdogan et al, 2006). Different marketing strategies would be developed and applied to each customer segments or clusters.

Cluster analysis techniques can be categorized as following (Tan et al, 2006)

1) Hierarchical vs. Partitional (nest or un-nested): Hierarchical techniques produce a nested sequence or partitions with a single all inclusive cluster at the top and single clusters of individual points at the bottom. It is organized as a tree. Partitional techniques create one-level non –overlapping or un-nested partitioning of data. Each data object is in exactly one subset or subgroup.
2) Exclusive vs. Overlapping vs. Fuzzy: All exclusive clustering is when each object is assigned to a single cluster. If an object can simultaneously be assigned to more than one group, it is overlapping or non-exclusive clustering. It is used when an object can equally be assigned to any of the groups. Fuzzy clustering assigns membership weight between 0(absolutely doesn't belong) and 1(absolutely belongs) for every object to every cluster.
3) Complete vs. Partial: A complete clustering assigns every object to a cluster; while a partial clustering does not (Tan et al, 2006). The objects which are not assigned to any clusters can possible represent noises or outliers.

1.3.2 Steps in Cluster Analysis

Cluster analysis is generally started with observation measurements. Observations are measured on K variables. Observation similarity distances between each pair of observations are measured. Some algorithm will be employed to group the observations

into subgroups based on those observations similarities. Then clusters are formed. The goal is to create the clusters which have small with-in cluster variation, but large between-cluster variation. And finally clusters are compared. The differences between clusters can be seen from the representative values such as mean values of the input variables from each cluster. The steps are shown in Figure 1.2.

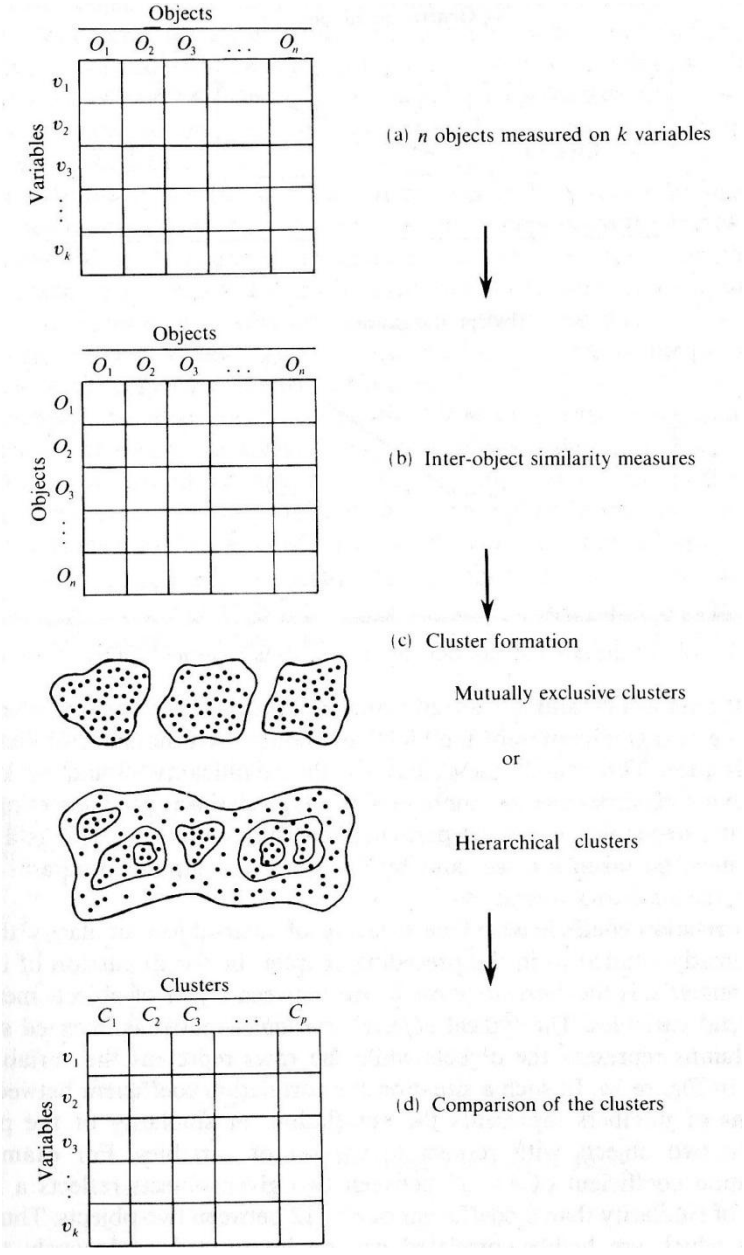

Figure 1.2 An Outline of Cluster Analysis Procedure. (Kachigan, 1991)

Unlike other data analysis methods, cluster analysis has been developed throughout the years in many disciplines; for examples, management sciences, marketing management, biomedical sciences, and computer sciences. There is no single dominant discipline. The purposes or the benefit of the cluster analysis depend on the type of the applications. For example, in marketing, cluster analysis may be used mainly to learn about market segments and to seek a better understanding of buyer behaviors by identifying homogeneous groups of buyers (Punj et al, 1983), in medical science, patients can be clustered based on symptoms to understand the causes and to help finding alternative therapies (McLachlan, 1992). In psychology, Clutter (2006) uses cluster analysis to understand the relationship between health risk and college students' health behaviors.

1.3.3 Clustering Evaluation

Selecting techniques or parameters for cluster analysis is not an easy task. Moreover, Morrison (1967) states that some of the methods that give statistically meaningful results will not necessarily give managerially meaningful results. Clustering is an unsupervised learning algorithm. There is no label (class) for the data. Its goal is trying to determine to which group each data in unlabeled data set belongs. There is no absolute best criterion to decide which clustering algorithms give the best clusters. It must depend on user's need. The best clustering techniques are those that can provide the results which are useful for the user's purposes. Cluster evaluation and interpretation are quite subjective. Though the clustering results can also be interpreted in different ways, the meaning of each cluster should be intuitive.

Each clustering technique defines its own type of cluster and requires different type of evaluations (Tan et al, 2006). Most clustering techniques have focused on numerical data. One of the popular cluster analysis techniques is K-means clustering. With numeric values, the definition of clustering does generally suggest the notion of similarity, dissimilarity or distance between data objects. Its goal is to minimize the distance between data objects in the same clusters and maximize the distance between data objects from different clusters. The K-means clustering can be evaluated using Sum of Squares for Errors (SSE). However, there are more difficulties in clustering with categorical data because there is neither real nor natural distance between categorical data. When there is no obvious distance, it can be "defined". However, it is not always easy especially in multidimensional spaces.

In general, a good cluster algorithm is the one that produces clusters which the intra cluster similarity is high, while inter cluster similarity is low. However, the measure of the similarity is also a challenge. There are several techniques and measurement for similarity to choose from. The type of similarity measure should fit the type of data (Tan, et al, 2006). Some measurement may be good for one dataset but not for the other. A cluster algorithm can also be applied to a data set with a natural cluster and produce poor quality clusters simply because a wrong similarity measures have been chosen.

When good quality clusters are defined, to get a general idea of how the clusters are different, the means and the variances of each cluster should be compared (Kachigan, 1991). Examining the representative values of the clusters will help in understanding the distinguishing values and characteristics of each cluster.

All clusters should have enough observations to be meaningful for the interpretation. Having too small or too big clusters can mean that that number of cluster selected is not appropriate for the dataset (Garson, 2009). Not only a small cluster can mean that the number of clusters selected is too large, but the small cluster can be an outlier or anomaly. On the other hand, having a cluster which is too large dominating the results can mean that the number of cluster selected is too small.

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Chapter 2 Literature Review

2.1 Cluster Analysis

2.1.1 Methodological issues in Clustering

Selecting what clustering technique to be used and/or what parameter to set are not trivial tasks. Several factors should be considered when performing cluster analysis. There is no formula for determining the proper technique (Tan et al, 2006). Moreover, sometimes the intended application can influence the type of clustering to choose. Some factors worth considering are as follows:

2.1.1.1 Number of Clusters

Choosing the number of clusters is one of the most important decisions in performing cluster analysis. Clustering always finds subgroups or clusters; however, determining which groups are meaningful is the significant task. Several techniques can be used for estimating the number of clusters. Some of which are very straightforward, while others are quite subjective. Alpaydin (2004) outlines some techniques for selecting the number of clusters as follows:

- The data can be plotted into two –three dimensional space and examined,
- Reconstruction error or log likelihood as a function of numbers of clusters can be plotted,
- Validation of the groups can be done manually by checking for the meaningfulness of the groups, in some simple dataset,
- Looking at differences between levels in the tree, a good split can be identified in hierarchical clustering.

Milligan et al (1985) examine procedures for determining the number of clusters in a dataset by running a Monte Carlo simulation on artificial datasets. Based on the assumption that the true numbers of clusters in the datasets are known, four hierarchical clustering methods and many stopping rules are examined using simulation. Some procedures work well, while others do not. The results from Milligan's study provide clear evidence that the performance of some cluster analyses may be data dependent. Therefore, researchers may have to try alternative techniques and specification to see which one will work best. Research is needed to guide on this process.

2.1.1.2 Clustering Algorithm

There are many algorithms available in the literature such as K-mean clustering, fuzzy C-mean clustering and hierarchical clustering. These algorithms are mainly for quantitative values. It has been shown that traditional algorithms are not appropriate for categorical data and many other algorithms have been introduced for categorical values. Ohn Mar Sun et al (2004) propose an alternative to k-mean clustering for categorical data; which is using the notion of "cluster center" to formulate the cluster problems for categorical data as a partitioning problem. Guta et al (1999) propose a novel concept of *links* (called ROCK) to measure the similarity/proximity between a pair of data points for Boolean and categorical attributes. The concept is naturally extended to *non-metric* similarity measures that are relevant in situations where a domain expert/similarity table is the only source of knowledge.

Ganti et al (1999) introduce "CACTUS"; which is a formalization of a cluster for categorical attributes by generalizing a definition of a cluster for numerical attributes. The technique requires two scans of the dataset and is a fast summarization based

algorithm. Zengyou et al (2002) suggest another clustering method for categorical attributes called "SQUEEZER". The algorithm reads each tuple or record ***t*** in sequence then either assigning ***t*** to an existing cluster (initially none), or creating ***t*** as a new cluster, which is determined by the similarities between ***t*** and clusters. It is extremely suitable for data stream.

2.1.1.3 Characteristics of the data set and attributes

There are various types of data, such as structured, graphed or ordered. Attributes are also 1) quantitative or nominal and 2) binary, discrete or continuous. The type of data set and attributes can dictate the type of algorithm to use. Similarity/Dissimilarity measures should be appropriate for the type of data being considered (Punj et al, 1983). For example, K-means algorithm can only be used on data for which an appropriate proximity measure is available and that allows meaningful computation of cluster centroids (Tan et al, 2006). For other algorithms, such as many agglomerative hierarchical approaches, the nature of dataset and attributes is less important. Some algorithms may not be suitable for some data type. Morrison (1967) shows how the scale used in measuring input variables will affect the results. Sometimes, data must be processed (i.e. to discretized or binarized) so that the similarity matrix can be calculated. The problem will become more complicated when the dataset have a mixture of different attribute types.

2.1.1.4 Noise and outlier

Outliers or noise can affect the performance of the clustering algorithms. In some techniques such as single linkage, outliers can result in joining clusters which should not be joined. Therefore, data might have to be preprocessed to remove outliers before

performing cluster analysis. Some algorithms, such as DBSCAN, **D**ensity-**B**ased **S**patial **C**lustering of **A**pplications with **N**oise, can detect or identify objects as noise and move them from clustering procedure (Tan et al, 2006).

2.1.1.5 Number of data objects

Clustering can be affected by the number of data objects. Cluster analysis requires powerful computing because computations can be extensive; especially as the number of objects increases. To include or exclude a certain observation can have an effect on the clusters' forms. Ideally, all observations, assuming no outliers, should be included in the clustering procedure so that the cluster results are a true representation of the dataset.

2.1.1.6 Number of attributes

Algorithms that work well in low dimensions may not work well in high dimensions. In other words, algorithms that work well when there are fewer attributes, such as 1-20 attributes, may not give a great result when there are a larger number of attributes such as a hundred different attributes. The relationship among attributes can also create difficulties in cluster analysis. Moreover, using a small number of attributes may be easier for clustering procedures; however, the results may not be useful. On the other hand, using many attributes at the same time may complicate the procedures. For example, Green et al (1967) discuss that while using only one attribute (such as income levels) is not enough; however, using 10-15 attributes (such as education, ethnic composition, physical distribution, etc.) for clustering may actually be very difficult to process. The algorithm will produce clusters; but, the resulting clusters may be useless in representing real data structures.

2.1.1.7 Algorithm consideration

Each clustering algorithm is different. The theories and idea behind each procedure make one algorithm good to one dataset/or purpose, but not the other. Several decisions must be made. For example, simple K-mean algorithm requires the specification of the number of clusters, while expectation maximization algorithm does not have this requirement. There are also techniques to define the values of various parameters, such as number of clusters. The theoretical support of the algorithm that performs the cluster analysis is important. Otherwise, the clustering results, even though the algorithm can produce an optimal cluster, will not be meaningful. Moreover, clustering algorithms usually have one or more parameters which should be set or selected by users; for example, choosing the number of clusters in simple K-mean clustering. Several trial and error attempts should be conducted in order to find suitable values for those parameters. This process of selecting parameter can become even more complicated because a small change in a parameter value can significantly change the clustering results. (Tan at el, 2006)

2.1.2 Anomaly Detection

Anomaly detection is the procedure of identifying observations whose characteristics are significantly different from the rest of the data or the population (Tan et al, 2006). These observations are called outliers or anomalies because they have attribute values that deviate significantly from the expected or typical attribute values. Applications of anomaly detection include fraud detection, credit card fraud detection, network intrusion, etc. Regardless of the domain, anomaly detection procedures generally involve three basic steps: 1) identify normality or what is normal by calculating some "signature" of the data, 2) determine some metric to calculate an observation's degree of

deviation from the signature or how much it is different or deviate from normal data, and 3) set some criteria/threshold which, if exceeded by an observation's metric measurement means the observation is anomalous (Davidson, 2002). A variety of methods or an option for each step has been used in various applications in many fields.

2.1.3 Application of Clustering

Clustering is a widely used technique in the area of marketing research, especially market segmentation, market structure analysis, and study of customer behavior. In the review of cluster analysis in marketing research, Punj et al (1983) have listed many marketing studies prior to 1983; which applied cluster analysis as their methodologies for understanding the market segments and buyer behaviors. Market segmentation using cluster analysis have been examined in many different industries, for instance, finance and banking (Anderson et al, 1976, Calantone et al, 1978), automobile (Kiel et al, 1981), education (Moriarty et al, 1978), consumer product (Sexton, 1974, Schaninger et al, 1980) and high technology (Green et al, 1968).

Another examination of the usefulness of cluster analysis is for test market selection. Green et al (1967) use cluster analysis for test marketing to ensure projectability (or predictability) of the test marketing results. The responses or the results of the test program in the area selected for marketing tests provide a reasonable and accurate indication of the results or responses from customers in the larger geographic area. Therefore, cluster analysis is used for choosing an appropriate set of test cities or areas.

Cluster analysis can be used to extract information about markets and customers. Erdogan et al (2006) use cluster analysis to understand the readership patterns of the

medical journal. Shih et al (2003) study the customer relationship management using k-means clustering methodology to group customers with similar lifetime value or loyalty in hardware retailer business. The results can help companies to gain a better understanding of clusters so they can allocate the appropriate resources to ensure the effectiveness of marketing investment.

Cluster analysis can also be used to extract information from a single group or segment; such as to define characteristics or behaviors or members in sub-groups. For example, Lim et al (2006) use the case survey methodology to study the characteristic of international marketing strategies of a multinational firm and to group them by using hierarchical clustering via Ward's method. Wziatek-Kubiak et al (2009) use cluster analysis to investigate the differences in innovation behaviors among manufacturing firms in three countries in Europe. Five types of innovation patterns are detected and similarities and differences are highlighted.

Using different attributes as inputs for cluster analysis can create many useful and interesting results. For example, Srivastava et al (1981) use hierarchical clustering approach to cluster the products based on substitution-in-use in market structure analysis. Two important factors for the analysis are the degree of substitutability of the product and method used to analyze. Morwitz et al (1992) examine sales forecasts based on purchase intentions utilizing various methods of partitioning to determine whether segmentation methods can improve on the aggregate forecasts. Chang et al (2005) try to investigate the expression modes typically used by consumers by using hierarchical clustering analysis to re-categorize the total set of expression categories. They are clustered into meaningful and distinct expression modes to help in the understanding consumers' expressions.

These research studies demonstrate that various types of attributes can be used as inputs for cluster analysis. In the social sciences, cluster analysis is used similarly to market segmentation in Marketing. For example, Hirschberg et al (1991) with attributes related to social and political factors (i.e. political rights, real domestic product, life expectancy, etc) apply cluster analysis for measuring welfare and quality of life across countries. Ferro-Luzzi et al (2006) use cluster analysis in combination with factor analysis and logistic regression to help in the measurement of poverty. Factor analysis is used to find the common factors for some aspect of multidimensional poverty. Cluster analysis then determines subgroups by using the factor derived. The determinant of poverty is identified by using logistic regression.

Cluster Analysis has been extensively used in marketing and many other fields to understand the patterns and behaviors of the dataset. Though, there is much potential in the usage of cluster analysis to understand the nature of accounting transactions as very few studies have been performed.

2.2 Fraud prediction using data mining techniques

2.2.1 Management Fraud Prediction

Research on fraud prediction models is discussed in this section. For predicting management fraud, most models employ either logistic regression or Neural Networks.

Bell et al (2000) develop a model useful in predicting fraudulent financial reporting. The authors propose a working discriminant function for the conceptual model from Loebbecke et al (1989). Using a sample of 77 fraud, and 305 non fraud control firms, they develop and test a logistic regression model to estimate the likelihood of

fraudulent financial reporting for an audit client, conditioned on the presence of fraud-risk factors.

Fanning et al (1995) propose an alternative approach, Artificial Neural Networks (ANNs), for detection of management fraud. Neural networks are designed using both generalized adaptive neural network architectures (GANNA) and the Adaptive Logic Network (ALN). Using the same data set as Bell et al (2000), the prediction accuracy is 89% for GANNA and 90% from ALN.

Green et al (1997) examine the use of neural networks (NN) as a means of detecting financial statement fraud in the revenue and collection cycle of publicly held manufacturing and merchandising companies. Five ratios (Allowance for doubtful account/ Net sales, Allowance for doubtful account/ AR, Net sales/ AR, Gross Margin/ Net sales, AR/ TA) and three accounts (Net sales, AR, Allowance for doubtful account) are used. Eighty six (86) fraudulent firms and 86 non-fraudulent firms are used as samples. Models' performances or accuracy are ranked from 32% to 62%.

Deshmukh et al (1997) develop membership functions and fuzzy rules for assessing risk of management fraud using the statistical significance of each red flag and theoretical model. Using the same data set as Bell et al (2000), this model gives a similar result.

Fanning et al (1998) propose the use of self-organizing Artificial Neural Network (ANN), AutoNet, to develop a model for detecting management fraud using publicly available financial information. From twenty possible indicators of fraudulent financial statement, the neural network model selects a discriminant function that was statistically successful on a holdout sample. The model's prediction accuracy is 63%. The neural net

model performs better than linear and quadratic discriminant analysis and logistic regression.

Lin et al (2003) evaluate the utility of an integrated fuzzy neural network (FNN) for fraud detection. FNNs are a class of hybrid intelligent systems that integrate fuzzy logic with Artificial Neural Network. All of the variables used are financial ratios. The FNN developed in this research outperformed most statistical models and artificial neural networks (ANNs) with approximately 76% accuracy.

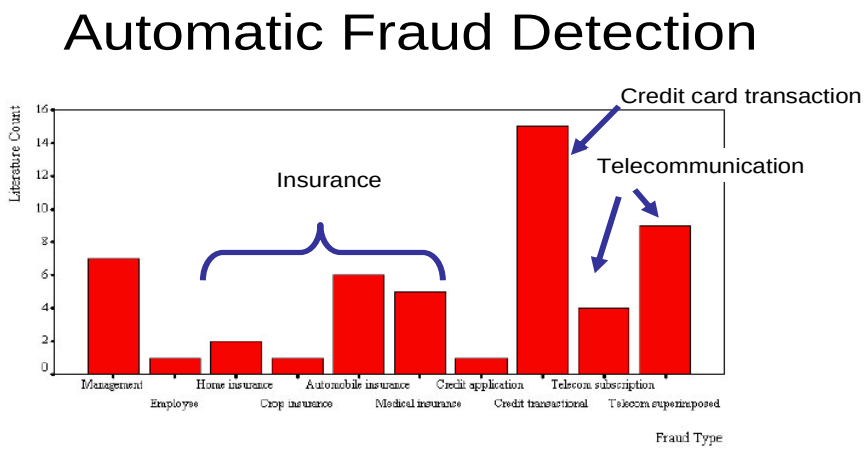
Though, several fraud prediction models mentioned previously can give very good prediction performance, the majority of papers extend the work of Bell et al (1991). Three papers (Bell et al, 2000, Fanning et al, 1995, Deshmukh et al., 1997) use the same data set to test model performance. The data used consists of a set of questions administered to KPMG partners. These models have two major disadvantages, which were derived from the use of this data set. First, these three models' performance could have been overstated due to possible hindsight bias inherent in the judgment made by the auditors associated with fraud engagements (Bell et al, 2000). Secondly, the data is not publicly available. Therefore, the application of these models to general cases may be difficult, if not impossible, and it might not be cost effective to do.

Prediction in other models is generally in the 50-65% range. This level of prediction performance is not high. Though Lin et al (2003) give a generally high prediction performance; the use of only groups of variables related to account receivables is a limitation. Moreover, the fraud sample size is small. Account receivables have already been proven as a good predictor of fraud. Using variations of the AR ratios would

not be much of a contribution to the literature. Better and more accurate models for fraud prediction are needed.

2.2.2 Other Types of Fraud Prediction

There are numerous automated techniques for fraud detection frequently being developed in many business fields, such as credit card fraud detection, telecommunication fraud detection, and computer intrusion detection. Phua et at (2005) present the bar chart of the academic papers categorized by fraud types in Figure 2.1.



Phua, C., V. Lee, K. Smith and R. Gaylor, 2005, A Comprehensive Survey of Data Mining based Fraud Detection Research, available at http://www.bsys.monash.edu.au/people/cphua

Figure 2.1 Automatic Fraud Detection

Credit card transactional fraud detection has received the most attention from researchers. Research papers are mainly from the computer, information system, or engineering domains. Phua et al (2005), a comprehensive survey of Data Mining-based Fraud detection Research, is also a paper from the information systems domain. Though there are some weaknesses in the paper regarding management fraud, this survey presents a couple of interesting points. First, the management data sets are smaller comparing to

other data sets in credit card fraud, telecommunication fraud, etc. All research in management fraud has less than 500 observations in the sample, while credit card transaction data and telecommunication data have over millions as the sample size. Second, the number of specific attributes and variables used for detecting management fraud is also small and mainly a specific type of information. Management fraud data is typically financial ratios, using information such as account receivables, allowance of bad debts, and net sales. The data used in other fraud types is more varied.

2.3 Continuous Auditing

Continuous auditing (CA) is a methodology that enables independent auditors to provide written assurance on a subject matter using a series of auditors' reports issued simultaneously with, or a short period of time after, the occurrence of events underlying the subject matter (CICA/AICPA 1999).

While the ultimate objectives of traditional and continuous auditing are the same, continuous auditing has a number of distinct advantages over the traditional audit. Firstly, continuous auditing may be deployed more frequently to improve the timeliness and relevance of results. Secondly, the incremental cost of verifying more transactions is relatively small. And thirdly, it may improve the quality of audit evidence by increasing the scope of transactions tested and providing evidence about these transactions in a more timely fashion (Brown et al, 2007).

Advanced information technology and electronization of business drives the need for continuous auditing and the use of technology in the auditing process (Vasarhelyi et al, 2003, Braun et al, 2003, Kogan et al, 1999, Rezaee et al, 2002., Vasarhelyi et al, 2004). The accounting profession, the regulatory agencies and investors are demanding

firms to release more accurate, timely, and detailed information concerning their operations. Information technology nowadays has advanced to the point where users can get more relevant and reliable information in or close to real-time.

Hunton et al (2002) find that more frequent reporting enhances the usefulness of information for decision making, improves the quality of earnings, reduces management's aggressiveness to manage earnings, and reduces the stock price volatility. Their study provides evidence of a positive correlation between frequent reporting and usefulness of the report to the decision maker. Rezaee et al (2002), Flowerday et al (2005), and Alles et al (2004) suggest that real-time financial reporting will necessitate continuous auditing. Also increasing frequency of disclosures will drive the nature of the audit process to ensure the reliability of the disclosure (Elliott, 2002).

Braun et al (2003) suggest that computer-assisted audit tools and technologies may help enabling detection of problems (i.e. errors and/or anomalies) as they occur, rather than at the end of the period. Then management will be able to find the solutions or strategies to eliminate or reduce the problem in the timely manner. Moreover, an improved quality of reports and the availability of the information will help the investors as well as analysts to monitor the firms more effectively. More timely detection of anomalies within business and accounting processes is a distinct benefit of continuous auditing (Brown et al. 2007).

The complexity of the business operation is also another factor driving the demand for the continuous auditing. Outsourcing and Electronic Data Interchange (EDI) have amplified the need for integrity of the transaction (Van Decker, 2004, Vasarhelyi et al, 2004). Information systems from business partners are usually linked or

interconnected so that it can facilitate their operations and cooperation. They need to be able to rely on the data received from or forwarded to their business partners. Therefore, the integrity and reliability of the data is important making continuous auditing a progressively increasing necessity.

The change in the legislation, (i.e. especially Sarbanes-Oxley Act of 2002) is another factor that drives the demand for continuous auditing. SOX section 404 intended to force companies to document and test their internal controls over financial reporting and assign management the responsibility for ensuring the accuracy and the effectiveness of the internal controls. With this rule, the management's internal control report will:

1) State the responsibility of management for establishing and maintaining an adequate internal control structure and procedures for financial reporting; and
2) Contain an assessment, as of the end of the fiscal year, of the effectiveness of the internal control structure and procedures for financial reporting.

This certification should be included in annual and quarterly SEC filings. Section 404 might be considered the most critical part of SOX. Therefore, senior management should be willing to invest in technology solutions (e.g., business performance management solutions, internal compliance dashboards/portals, enabling workflow, replacing/upgrading financial systems, and consolidating ERP systems) to improve compliance with the SOX. Because of SOX section 404's requirements; it is believed that continuous auditing will facilitate the overall evaluation and testing of internal financial reporting controls. It will provide the necessary assurance to the key executives who will have to make the Section 404 certification. Compliance with Section 404 may initially be interpreted as the requirement of documenting internal controls; however, management

will later realize that an integrated view of controls is needed for their efficiency and effectiveness of their operation. Warren et al (2003) find that internal auditors are interested in continuous auditing techniques and how it can assist their work; however, they need guidance in the implementation. In the future, internal controls will be continuously monitored.

Vasarhelyi et al (2004) suggest that continuous auditing and analytic monitoring techniques may assist SOX section 404 compliance by

(1) Providing evidence that controls are functioning and providing understanding of the consequences of ineffective or nonoperational controls,

(2) Repeating data operations to assure controls are working and

(3) Querying specially designed controls to assure that they are operating.

SOX section 409 mentioned the need for "real-time reporting." Currently, it is interpreted as a requirement for the acceleration of periodic Securities Exchange Act of 1934 filings (e.g. quarterly report Form). Though "real-time" is not considered in the same sense as in information technology domain just yet, it will become closer and closer in the future. For example, Securities and Exchange Commission (SEC) voted on December 2005 to revise deadlines for filing periodic reports and create a new category of large accelerated filers. The revised deadlines are listed in Table 2.1. This section may be further interpreted as the rule requiring deadlines even closer to real time reporting in the future. This section could be seen as a catalyst for continuous auditing. The greater the need of the real-time reporting leads to increased demand for continuous auditing.

Table 2.1 Revised Deadlines for Filing Periodic Reports

Category of Filer	Revised Deadlines For Filing Periodic Reports	
	Form 10-K Deadline	**Form 10-Q Deadline**
Large Accelerated Filer ($700MM or more)	75 days for fiscal years ending before December 15, 2006 and 60 days for fiscal years ending on or after December 15, 2006	40 days
Accelerated Filer ($75MM or more and less than $700MM)	75 days	40 days
Non-accelerated Filer (less than $75MM)	90 days	45 days

Accessed from: http://www.sec.gov/answers/form10k.htm

Vasarhelyi et al (2004) develop a theoretical framework for continuous auditing. This framework consists of a four level of analysis, (1. transaction evaluation, 2. measurement rule assurance estimate assurance, 3. consistency of aggregate measures, and 4. judgment assurance), characterized by audit objectives, procedures, level of automation and paradigms used. Vasarhelyi et al (2004) also identify tools used in new continuous auditing assurance technology to detect variances or exceptions from systems' norms. These tools are as following.

- Continuity Equations: Using business process knowledge and related performance measures to evaluate the reasonableness of actual transactional information.
- Transaction tagging : Identifying transaction by using tags allowing the transaction flow from one application to the next to be evaluated for data accuracy and integrity
- Time-series and cross-sectional statistical analyses: Developing models to compare against actual results.

- Automatic confirmations: Vasarhelyi et al (2004) assert that automatic confirmation procedures have the potential to change the nature, scope, and procedures of an audit because of their ability to fulfill audit objectives at the transaction level.
- Control tags: Containing a range of information can help mark data paths or serve other audit purposes to provide assurance about transaction processing.

Groomer et al (1989) examine the use of an Embedded Audit Module (EAM) approach to capture information about exceptions and violations to the defined data access restrictions in continuous auditing of database application. With EAMs, violation and exception information can be detected on a real-time basis. All events (transactions) can be screened and the extent of compliance testing may be reduced.

Debreceny et al (2003) outline the development of embedded audit module alerts for ten potential types of fraud and present the evidence that some of the alerts interfered with smooth operation of the accounting system. Dull at al. (2004) proposed an application of control charts previously used for manufacturing process monitoring to continuous auditing.

Examining the effects of adding continuous auditing processing loads to the overall system, Murthy (2004) concludes that aggregate function controls have very detrimental effects on system performance; therefore, system capacity planning is important.

Several enabling technologies, including belief functions, databases, expert systems, intelligent agents, neural networks, real-time accounting, and XBRL/XML, have been identified for continuous auditing (Brown et al, 2007).

Belief functions can be a good method for aggregating audit evidence (Sun et al, 2006; Gillett et al, 2000; Srivastava et al, 2000; Srivastava et al, 1992; Shafer et al, 1990). Shafer et al (1990) compare the Bayesian formalism with the belief-function formalism from the perspective for auditing to suggest that it can be an alternative choice for auditors. Shafer et al (1992) go on to relate or to suggest using - belief functions for structuring audit risk. Gillett et al (2000) demonstrate how statistical audit evidence obtained by attribute sampling may be represented as belief functions. Srivastava et al (2000) describe the evidential network using a belief function model and a decision-theoretic model for Web Trust assurance services. Sun et al (2006) provide the examples, from the perspective of auditors, of how the Dempster-Shafer Theory of Belief Functions can be implemented for information system security risk analysis. Because of the complexity of the environment where continuous auditing must cooperate, the belief function framework provides a structured, yet tractable approach to risk assessment and proves useful for continuous auditing (Brown et al, 2007)

Kogan et al (1999) suggest that continuous auditing is only possible if the implementation is fully automated and the system allows instant access to relevant events and their outcomes. Rapid improvement in the information technology and the reducing cost of hardware can help facilitate the growth of continuous auditing.

Rezee et al (2002), realizing the complexity and challenges concerning the standardization of data sources in building continuous auditing capacity, propose a model that does not require an ERP data warehouse, but require an audit data mart. Data will be collected, transformed and stored in an audit data server for data marts for easy access, analysis and report. Rezee et al (2002) also outline the characteristics of an integrated

audit data mart as follows; 1) provide integrated query analysis and reporting, 2) have an easy-to-use product line, but powerful enough for sophisticated users, 3) can export the result of the queries to common spreadsheets and database systems, 4) have a query engine capable of retrieving and processing large volume of data, 5) have data aggregation and multidimensional database capability, 6) can perform advanced statistical modeling and data exploration, 7) have data visualization capability for data mining exploration and identification of patterns and trends in the data set. Murthy et al (2004) suggest a similar list of necessary characteristics for continuous auditing, including 1) a highly reliable client system which can provide necessary information to the auditor in a timely manner, 2) the electronically accessible audited subjects, 3) auditor who is proficient in information systems computer technology and what is to be audited, 4) automated procedures reliably providing the needed audit evidence, and 5) high level management or executive who champion continuous auditing.

An expert system is one of the enabling technologies which has been applied in a variety of auditing tasks. The applications have been developed for tasks in many steps of the audit process. Gillett (1993) proposes a system called "ADAPT", an automated dynamic audit program tailoring using an expert system. A number of expert systems were developed and used in accounting firms including Deloitte Touche's Audit Planning Advisor (Zhao et al 2004, Brown 1991), Price Waterhouse's Planet (Zhao et al 2004, Brown 1991), Arthur Andersen's WinProcess (Zhao et al 2004, Brown 1991) and KPMG's KRisk (Zhao et al 2004; Bell et al 2002; Brown 1991). Baldwin et al (1993) study the impact of expert system audit tools on auditing firms and find that successful

application of AI to auditing tasks are mostly for structured repetitive tasks where the human expertise is not extremely hard to acquire.

An intelligent agent is another enabling technology that can facilitate - continuous auditing. FRAANK (Financial Reporting and Auditing Agent with Net Knowledge) system is an example of intelligent agent, which acquire, parse, and covert financial information available on the WEB to XBRL and can automatically be processed to achieve the audit objectives (Kogan et al, 2002). Woodroof et al (2001a, 2001b) describe the usage of an intelligent agent to continuously assure debt covenant compliance. These systems provide evidence that intelligent agents can be used in continuous auditing.

Another type of intelligent agent used in continuous auditing is a Neural Network. Although the black box nature of neural networks poses some issues, the ability of neural networks to quickly tag unusual transactions for additional screening could prove useful in minimizing the impact of continuous auditing on the performance of accounting systems (Brown et al, 2007). Neural networks have long been used in transaction screening by banks, credit card companies and insurance companies (Baker 2005; Viaene et al. 2002). Several studies in the field of continuous auditing propose the use of Neural Networks for error and fraud detection (Lin et al, 2003, Fanning and Cogger, 1998, Fanning et al. 1995). Some studies examine the use of this technique for analytical review. Coakley et al (1993) seed material errors in the monthly data and applied the artificial neural network to the ratio analysis for error detections. Koskivaara (2000) compares the analytical procedure using regression and the integrated analytical procedure using the Artificial Neural Network (ANN) which is embedded in the continuous auditing environment. In addition to error and fraud detection, neural

networks have also been used in making control risk assessment. Ramamoorti et al (1999) investigate whether the neural network can enhance internal auditors' risk assessments. Davis (1997) also proposes a similar line of work, a prototype expert network to support a complex audit judgment task (the internal control risk assessment).

2.4 Conclusion and Research Question

Never ending demands from users have always been the driving force of the technology development. When existing needs are fulfilled, users start to develop new and usually more complicated needs. For examples, in the early years of computer systems, with the limitation of the system capability, users may only wish and obtain weekly or monthly summary information. When the weekly or monthly information was obtained, the users may start to develop the need for daily, hourly and eventually for on-demand summary information. The availability of the information technology and user needs have created the need for more innovative ideas.

The accounting profession is not an exception. The audit profession started to look for more advanced and innovative ideas to be adopted in performing the audit tasks. Several advanced and computation intensive techniques have been tested or applied with accounting data (such as Artificial Neural Network, Belief functions, etc.). On one hand, new technologies can be developed out- of-the box, tested and implemented. However, this process can take long time. On the other hand, another possible alternative is to borrow techniques which are popular from other disciplines. One of such technique that has not often been applied to the accounting is cluster analysis. It is promising not only as a method to acquire information (as in data exploration) but also a method to detect anomalies.

The research question that this dissertation deals with is:

"How can we apply cluster analysis in auditing?"

Three examples will demonstrate to the readers how this technology can be implemented in the audit using real world data from real companies. First example, using the data from an international bank, will demonstrate how the cluster analysis can be used for data exploration to gain additional knowledge about the data set. The second and the third examples, using the data from an insurance company, will provide readers with the first look of how the auditor can use this technique for the auditing tasks.

The ultimate purpose of this dissertation is to provide guideline of how the cluster analysis can be implemented with accounting data, how the results can be interpreted and utilized.

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Chapter 3 : Cluster Analysis for Exploratory Data Analysis in Auditing

3.1 Introduction

Understanding the data is an important step in any analysis. When planning an audit, auditors need to understand the client and their data in order to plan effective and efficient audit procedures. There are several methods that auditors can use to obtain information and knowledge about the client. For example, auditors can calculate statistical values such as maximum, minimum, median and standard deviation. In addition to these classic statistical methods, powerful data mining methods are gaining popularity as computer systems become less expensive. For example, cluster analysis is used as an important exploratory tool for knowledge discovery.

This research study applies a conceptual clustering tool to a dataset from a real company. The objective is to demonstrate the usage of this method for Exploratory Data Analysis (EDA) in a real world setting. The chapter begins by providing an explanation of exploratory data analysis, and discussing how cluster analysis can be used for data exploratory purposes by outlining the audit problems the sample company is facing. The structure of data set, the research methodology, and the results are then presented.

3.2 Exploratory Data Analysis

Practical data analysis can be divided into two phases: exploratory and confirmatory (Tukey, 1977). Exploratory data analysis emphasizes flexible searching for clues and evidence, whereas confirmatory data analysis stresses evaluating the available evidence (Hoaglin et al, 1983). The method of choice for evaluating data is a matter of philosophy. Exploratory data Analysis (EDA) can be characterized as a search for

regularity or structure among objects in an environment, and the subsequent interpretation of discovered regularity (Fisher et al., 1986; Tukey, 1977). The most common forms of exploratory data examination are classical statistical and special graphics displays. Many different tools can be used for representing structures in data, using the classical method; for example, numeric summaries (i.e. in the form of means, median, min, max, summation and etc) and statistical distributions (i.e. stem-and-leaf displays, bar graphs, and various kinds of graphs).

With the advent of advanced technologies and the decreasing cost of computer systems, a technique of using a series of Artificial Intelligence (AI) methods for exploratory data analysis is becoming more popular. These techniques use AI for machine learning. The major distinction between methods of machine learning and statistical data analysis is primarily due to differences in the way techniques of each type represent data and structure within the data (i.e. Methods of machine learning are strongly biased toward symbolic data representation.) (Fisher et al, 1986). Whether using statistical or machine learning methods, the objective of the data exploratory task is to construct classification schemes over an initially unclassified set of data.

3.3 Cluster Analysis for Data Exploratory Purposes

One alternative to using machine learning methods for data exploratory purposes is to use cluster analysis. Fisher et al (1986) defines the task, "the abstract clustering task", as follows:

> *The Abstract Clustering Task*
> *Given: A set of object, 0.*
> *Goal: Distinguish clusters (i.e., subsets of O) $S_1, \ldots, S_n$, such that intra cluster object similarity of each S_i tends to be maximized, and the inter-cluster object*

similarity over all S_j's tends to be minimized. A collection of clusters is termed a ***clustering***.

Michalski (1980) considers conceptual clustering as an extension to the method of numerical taxonomy. Sokal et al (1963) define numerical taxonomy as a classification system in biological systematic which deals with grouping by numerical methods of taxonomic units based on their character states rather than using subjective evaluation of properties. The similarity between two objects is the value of a numeric function applied to the descriptions of the two objects (Everitt, 1980).

The numerical taxonomy technique implicitly assumes that objects (or observations) can be represented using continuous values. However, not all objects (or observations) can be measured in term of continuous values. There are four general levels of measurement (nominal, ordinal, interval and ratio) which lead to four kinds of scales (Kerlinger et al, 2000). The lowest level of measurement is *nominal measurement*, which is for nominal categories. For example, gender can be categorized into male and female; religion can be categorized into Catholic, Protestants, Buddhist, Muslim, and others. The second level of measurement is *ordinal measurement*. It requires that the objects of a set can be rank ordered on an operationally defined characteristic or property (Kerlinger et al, 2000). For example, customer satisfaction can be ranked using high, medium and low. In this example, it is possible to say high > medium>low. However, it does not give information on how different each scale is from others. The third level of measurement is *interval measurement*. In addition to having the characteristics of nominal and ordinal scales, interval has numerically equal distances between each level of the interval scale for the property being measured (Kerlinger et al, 2000) and can be

added and subtracted. For example, height, weight and age can be considered as interval measures. The highest level of measurement is *ratio measurement*. In addition to containing characteristics of nominal, ordinal, and interval measures, ratio has an absolute or natural zero. It means if an object is measured as zero on the ratio measurement, it has none of the property being measured.

Some objects can be measured using multiple measurements; for example, if the object is a person, values (or variables, or attributes) of interest can be age, height, weight, marriage status, educational background, race, etc. Some of these variables are ordinal measures (i.e. age, height and weight) and others are nominal values (i.e. marriage status, education background and race). To use a numerical taxonomy to represent similarity among people will be a challenge because these objects are represented with several types of measures.

Moreover, though the numerical taxonomy techniques are very useful, the resulting clusters or groups may not be easily characterized in a generalized conceptual language that can be used to hypothesize about future observations (Fisher et al, 1986). Michalski (1980) addresses the problem of determining conceptual representations of object clusters and defines conceptual clustering.

Given a set of concepts, C, which may be used to describe structures within a object set O, Michalski(1980) defines the similarity between two objects, A and B, as

$$Similarity(A,B) = f(A',B',O',C).$$

To explain in simple terms, the similarity between two objects depends on the quality of concepts used to describe them. The conceptual clustering defines the similarity between objects as a set of values common to all object of an object group.

Cluster Analysis has been extensively used in marketing and many other fields to understand the patterns and behavior of the dataset. For example, Erdogan et al (2006) examine consumer media habits by utilizing cluster analysis to understand readership patterns of a medical journal. The results of this type of study help interested parties such as the pharmaceutical industry to allocate appropriate resources to their marketing campaigns. Chang et al (2005) try to investigate the expression modes typically used by consumers by using hierarchical clustering analysis to re-categorize the total set of expression categories. The categories are clustered into meaningful and distinct expression modes. Lim et al (2006) use the case survey methodology to study the characteristics of international marketing campaigns of multinational firms and to group them using hierarchical clustering via Ward's method. Srivastava et al (1981) use a hierarchical clustering approach to cluster products based on a substitution-in-use in market structure analysis. Two important factors for the analysis are the degree of substitution of the product and the method. Morwitz et al (1992) examine sales forecasts based on purchase intentions utilizing various methods of partitioning to determine whether segmentation methods can improve the aggregate forecasts. Shih et al (2003) study the customer relationship management using k-means clustering methodology to group customers with similar lifetime value or loyalty in hardware retailer business.

Although there is much potential in using the cluster analysis on accounting data to understand the nature of transactions, there have been very few studies using this approach. Therefore more research is needed in this area.

3.4 The Audit Problem

This research study deals with a large international bank that identified transitory accounts as a major area of risk. Transitory accounts acts as a temporary resting places for bank transactions that cannot be completed immediately after being entered into the bank's system. The transaction is kept in a transitory account until the issue is resolved. Problems involving the transitory accounts may include a non-existent destination account for money transfers, higher transaction amount than the balance of the account, an inactive account, etc. Once the problem is resolved, the transaction is cleared. The remaining balance should then be "0".

The audit / management questions involve:

- Why does a transaction end up in transitory account?
- What was done to resolve the issue with the transaction?
- Was the appropriate action/change taken for the transaction proper?

Questions about what happens to transactions posted to transitory accounts are of great concern to the bank. Large incorrect entries could eventually create materially incorrect financial statements and substantive losses due to fraud or error. Consequently transitory accounts are included in a continuous auditing program aimed at monitoring key accounts and filtering potentially fraudulent transactions.

Little information is known about the transitory account's regularity and/or behavior. Therefore, it is a suitable scenario for exploratory data analysis. The auditor will gain understanding about these transitory accounts and identify possible risks and problems with the system.

3.5 Data

3.5.1 General Information

The sample transaction dataset covers the period from Jan 2008-Dec 2008. It encompasses information from 16 transitory accounts that have been pre-selected by the bank as the accounts of interest. A detailed description of each account given by the bank is listed in Table 3.1. The purpose and origin of each transitory account is different. For example, account 302 is for operations in process (which is a form of inter-departmental transfer); account 61930 is for wire transfers for financial applications; account 70050 and 70068 are for return of inter-departmental transfer. No matter where these transactions originated from, they are posted to the transitory account because the system cannot complete the transactions at the time they are presented. The problems can be for various reasons, including incomplete account numbers, incorrect account number, insufficient funds, etc.

Table 3.1 Detail Information of the Transitory Accounts

Account Number	Description
302	Operations in process : inter-departmental transfer
1155	Banker's check still outstanding
5738	(-) DAV (clearance) debit reclassification : checking acct
21776	Return of the check paid by clearing house
21830	Adjustment DAD (clearance of compensation) TITULOS/check/DOC
32360	Incorrect cash in treasury (maybe bulky multi-purpose acct)
45136	FAI : Pending operations in process
58122	SPB (cleaning house for TED) : credits between banks resubmitted
60836	Rejected received TED
61042	Clearance credit reclassfication
61930	Wire transfer for financial application
66613	(-) reclassification of debit CY (name of system) to correct wrong classification
68128	USB (department of process) occurences debtors
70050	Returns of inter-departmental transfer : one dept charges the other and turned out to be wrong so returned.
70068	Returns of inter-departmental transfer : one dept charges the other and turned out to be wrong so returned.
94870	Value received Bandeirantes TED STR

The frequency distribution of transactions in each account is presented in Table 3.2.

Table 3.2 Frequency Distribution of Transactions

Account Number (LANVFCDPCB)	Frequency	Percent
302	5652	1.41%
1155	688	0.17%
5738	49539	12.37%
21776	28741	7.18%
21830	23926	5.98%
32360	67187	16.78%
45136	73375	18.32%
58122	20395	5.09%
60836	91660	22.89%
61042	12114	3.03%
61930	1042	0.26%
66613	2426	0.61%
68128	19565	4.89%
70050	2715	0.68%
70068	889	0.22%
94870	503	0.13%
Total	**400417**	**100.00%**

3.5.2 Attributes

There are 16 attributes extracted from each transaction. The attributes are shown in Table 3.3.

Table 3.3 Attribute Information

Attribute Name	Description
LANVFCDUNID	Bank Unit No. Branch or administrator
LANVFCDPCB	Internal Acct #, Old branch #, and the table name
LANVFNUNSUE	(unique) Transaction #
LANVFDTLANC	Date of Entry in the table
LANVFDCCOMP	Comment
LANVFINDBCR	8 for debit, 9 for credit
LANVFVLLANC	Amount
LANVFVLSALD	(residual) amt (=balance)
LANVFDTULBX	Date of last entry on the balance
LANVFCDFUNC	Both 0 and 999999999 for automatic entry
LANVFCDORLC	System of origin that feeds the table. Validating from what system it is coming from. (Not used any more)
LANVFINRESP	Manual entry indicator (Not used any more)
LANVFCDSTPR	Status of processing (Not used anymore): 0-sent but not processed, 1-processed.
LANVFINEXCE	Account overage (Not used and more)
LANCDMULIUNID	Multi-Branch data (Not used any more)
LANCDEVENNEGO	Manual entry indicator (Not used any more)

The first three attributes, LANVFCDUNID, LANVFCDPCB, and LANVFNUNSUE, are identification types. They provide the branch number, account number and transaction number. Four of the attributes provide information related to date and monetary value when the transaction is originally posted and when the transaction is last posted on the transitory account. These attributes are LANVFDTLANC (original date), LANVFVLLANC (original monetary value posted), LANVFDTULBX (last date posted) and LANVFVLSALD (remaining balance).

Six of the attributes are no longer used by the bank; i.e. LANVFCDORLC, LANVFINRESP, LANVFCDSTPR, LANVFINEXCE, LANCDMULIUNID and LANCDEVENNEGO.

Two of the attributes give information on the nature of the transaction. LANVFINDBCR provides the information if the transaction is debit (8) or credit (9) type. LANVFCDFUNC specifies if the transaction is automatically entered or manually entered.

The attribute which appears to contain the most detailed information related to the transaction is the comment field or LANVFDCCOMP. This attribute is rich with information content. It can contain much of details such as account number, branch number, dates, reasons why the transaction is posted to the transitory account and etc. This information can be automatically entered by the system, manually entered by an employee of the bank, or a combination of both (i.e. partially automatic or partially manual). Generally, there is no pre-fixed format of how the comment should/could be entered. Though this attribute appears to contain valuable information, it is extremely difficult if not impossible to process the information for further analysis due to its free-field format. Therefore, a parsing procedure is developed to make the attribute readable and understandable to the computer system. The parsing procedure aims at breaking the comment into smaller and more manageable forms.

Because the structures of the comment are very different from account to account, (i.e. comment belonging to account #302 is totally different from those belonging to account #5738); the parsing procedure is tailored to a specific account. Once the

procedure is fully developed, it can be a prototype for developing such a procedure for other accounts.

3.5.3 Transitory Account for Debit Reclassification of Checking Account

Because of the differences in the structure of each comment, the parsing procedure developed is specific to the account. The account selected for this study is 5738. It is a transitory account for debit reclassification of a checking account. The reasons for selecting the account are the number of observations, which are large enough for the analysis, and the organized structure of the comment, which make it possible for the parsing procedures to be developed.

Each attribute is closely examined to determine if it can be used as the input for clustering procedures. Four attributes, LANVFINDBCR, LANVFCDSTPR, LANVFINEXCE, and LANCDMULIUNID, have only one possible value. Two date attributes, LANVFDTLANC and LANVFDTULBX, are shown with errors. They have "1900" as the year value. Therefore, they are excluded for the analysis. One attribute, LANVFDCCOMP, contains a free format field with comments from employees concerning the particular transactions. Two attributes, LANVFVLLANC and LANVFVLSALD are continuous values. Four attributes, LANVFCDFUNC, LANVFCDORLC, LANVFINRESP, and LANCDEVENNEGO from the total of 17 attributes are the remaining candidates for conceptual clustering. Therefore, the cluster analysis is performed on these remaining four attributes. The frequency distribution for this data is shown in Table 3.4.

Table 3.4 Distribution of four remaining attributes

LANVFCDFUNC	
0	49316
1120423	208
1173444	12
1180885	3
Total	49539

LANCDEVENNEGO	
603	49307
30397	6
(blank)	226
Total	49539

LANVFINRESP	
A	3
U	223
(blank)	49313
Total	49539

LANVFCDORLC	
11	222
15	109
29	3
41	49199
51	6
Total	49539

The parsing procedure for the account is presented in the next section, followed by the clustering procedure and the analysis of the results.

3.6 Parsing Procedure

The structure of the data file and an example of the values is presented in the Figure 3.1. The open comment attribute, LANVFDCCOMP, is rich with additional information. It is either automatically entered by the system, manually entered by a bank employees or a combination of both. In addition to account and branch number, LANVFDCCOMP generally contains information related to reasons why the specific transaction could not be completed and was consequently transferred to the transitory account. Possible reasons include incomplete account number, insufficient funds, inactive account, etc. When the information is passed on through computer systems, the data in this field is combined, making it unusable for further analysis. Therefore, the comment

field would be parsed so that the individual comment items would be used. Perl 5.10 is used for the parsing.

LANVFCDUNID	LANVFCDPCB	LANVFNUNSUE	LANVFDTLANC	LANVFCDTPTR	LANVFDCCOMP	LANVFNDBCR	LANVFVLLANC	LANVFVLSALD	LANVFDTULBX	LANVFCDFUNC	LANVFCDORLC	LANVFNRESP	LANVFCDSTPR	LANVFNEXCE	LANCDMULIUNID	LANCDEVENNEGO
1	5738	10200001941	15-Jan-08	0	AGENCIA = 1 CONTA = 2121828 72 - LCTO BLOQUEADO P/ CONTA PARALISADA 02030 DEVOLUCAO CHEQUE DEPOSITADO CN000121218282008011589406 2BCN21DA	8	900	0	16-Jan-08	0	41		1	0	0	603
1	5738	20200001941	15-Jan-08	0	AGENCIA = 1 CONTA = 2121828 72 - LCTO BLOQUEADO P/ CONTA PARALISADA 02030 DEVOLUCAO CHEQUE DEPOSITADO CN000121218282008011589406 3BCN21DA	8	805	0	17-Jan-08	0	41		1	0	0	603
46	5738	20800046941	15-Jan-08	0	AGENCIA = 46 CONTA = 2023243 03449 *ASSINATURA EDITORA ABRIL IB:88497554244039810310361601081501	8	51.4	0	18-Jan-08	0	41		1	0	0	603

Figure 3.1 Data Structure

The automatic or partially automatic comments are comprised of 2 -5 pre-set strings. These preset strings are separated from each other by blank spaces. Therefore, the blank spaces are used as the criteria for parsing these automatic and partially automatic comments.

The open comment attribute, LANVFDCCOMP, is separated from the other attributes for the parsing procedure. After the comment attribute is parsed into a set of smaller and understandable attributes, they are integrated back into the original list of attribute. The maximum of five (5) attributes would be created for each comment field. They are named “part1”, “part2”, “part3”, “part4”, and “part5”. The parsing procedure is shown in Figure 3.2.

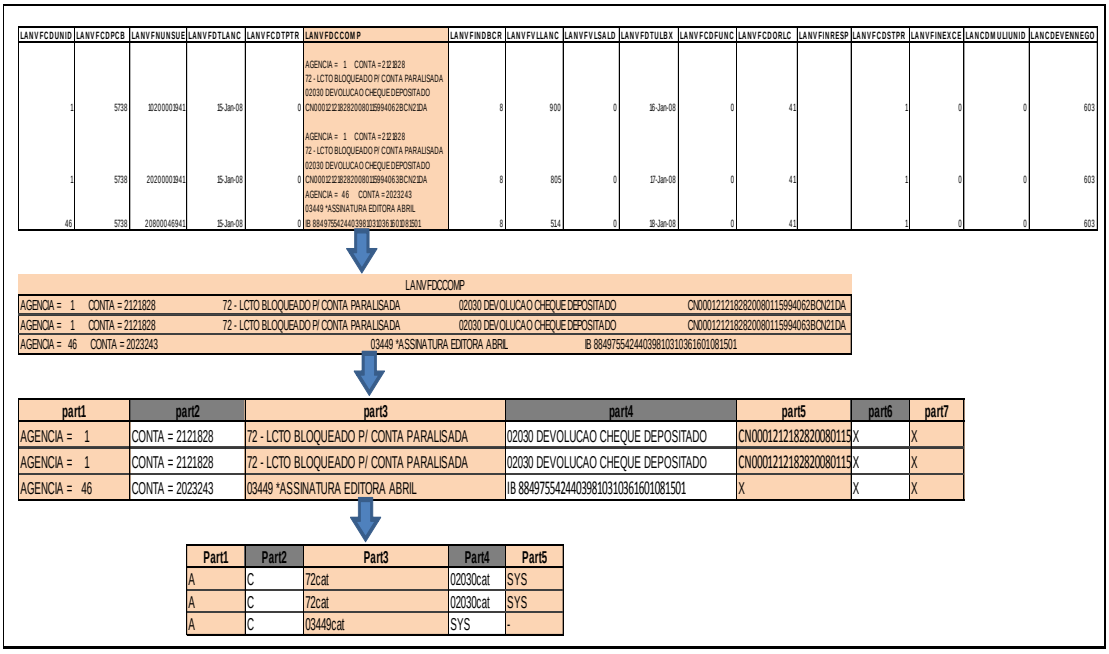

Figure 3.2 Parsing Procedure

3.6.1 Banks processing system

In addition to the pre-set strings, the comment field also includes a string which appears to be coded information transferred between various computer systems.

The main system of the bank is created from hundreds of smaller systems including legacy and newer systems. Therefore, the system has created a coding system for the between computer system transferring so that the system analyst can identify where and which system the information is from.

3.6.1.1 System Identification

The characteristic of this alphanumeric string is that it normally begins with characters and is followed by a string of numbers. An example of the system identification string is shown in Figure 3.3. The characters are a code name for a specific system, while a numeric string appears to have a structure or format. However, at present, it is not possible to parse the numeric string in order to get to the real information

embedded. Therefore, the string is coded as “SYS” to represent the information transferred with the computerized code. This string is also assigned to one of the parsed comment field (“part1”, “part2”, “part3”, “part4”and “part5”) depending on its respective position.

The parsing procedure is presented in Figure 3.2. In this illustration, in the last step, the system identification string is coded as “SYS”

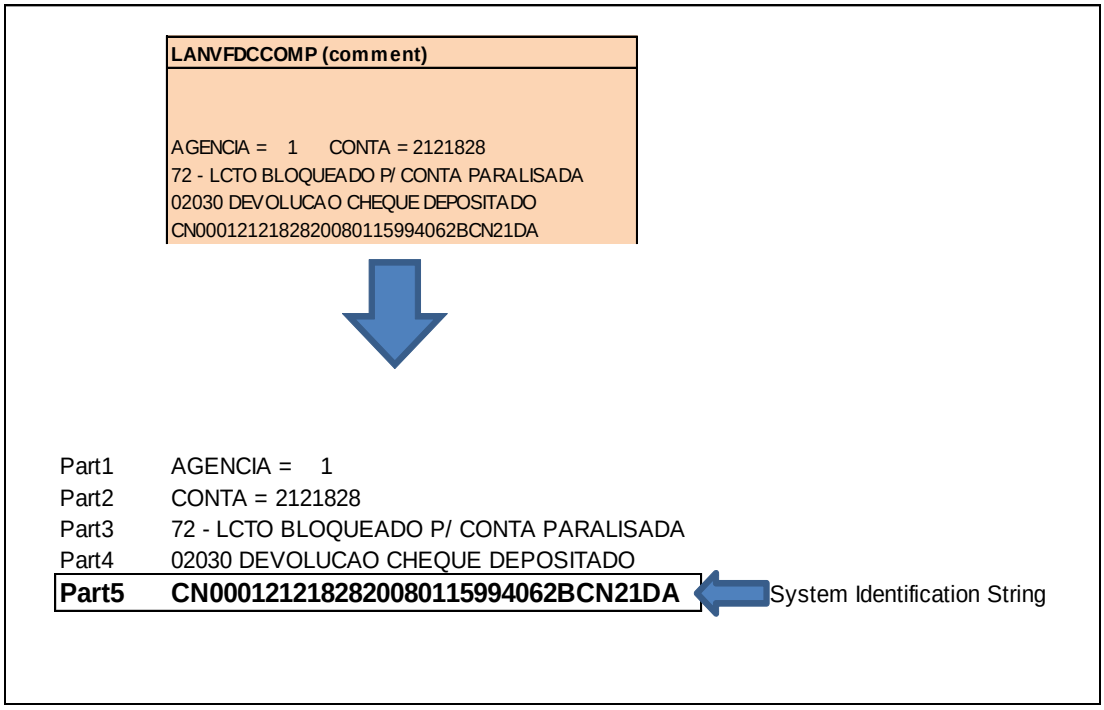

Figure 3.3 Example of System Identification String in the Comment

The parsed comment fields are used as the attributes for clustering. However, they are coded prior to feeding them to the data mining software to reduce the memory and disk requirements needed for the operation. Most preset strings are reduced from the 30-50 characters to less than 5-10 characters. Some preset strings are reduced to only one character. For example, “AGENCIA = 1100” is shorten to “a” to represent information about “agency” or branch. The objective at this coding stage is not to pick up information

on specific identity such as to pick up “1100” from the string “AGENCIA = 1100” but to recognize the pattern that this string refers to or gives information on agency number or branch number. In addition, as mentioned in previous section, the alphanumeric string representing the computer-coded information transferred between computer systems are coded as “SYS”. The steps taken to code the comment are shown in Figure 3.4.

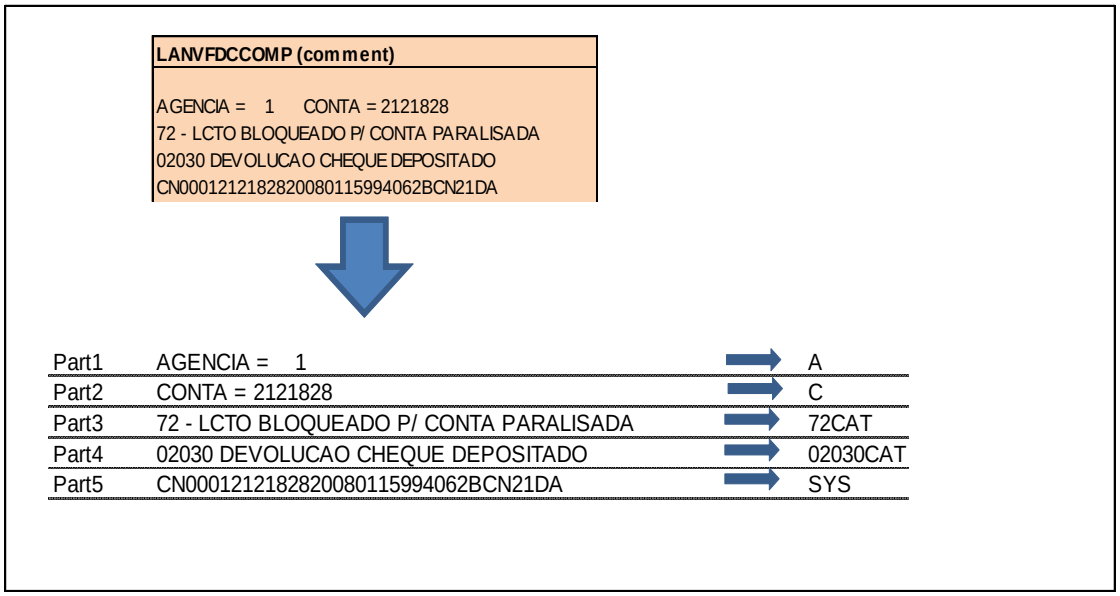

Figure 3.4 Comment Coding Illustration

3.7 Clustering Procedure

The parsed comment field is used as the input variable for clustering. Because neither the distribution of the input variables nor other parameters necessary for cluster analysis is known, the EM algorithm will be adopted for the clustering (Witten et al, 2005). EM algorithm, or expectation-maximization, involves two steps; 1) “expectation” is the calculation of the cluster probabilities, and 2) “maximization” of the likelihood of the distributions given the data. For this method, only the cluster probabilities, not the cluster themselves, that are known for each observation. They could be considered as

weights. Witten et al (2005) state if w_i is the probability that observation i belongs to cluster A, the mean and standard deviation for cluster A are

$$\mu_A = \frac{w_1 x_1 + w_2 x_2 + ... + w_n x_n}{w_1 + w_2 + ... + w_n}$$

$$\sigma_A^2 = \frac{w_1 (x_1 - \mu)^2 + w_2 (x_2 - \mu)^2 + ... + w_n (x_n - \mu)^2}{w_1 + w_2 + ... + w_n}$$

The EM algorithm converges toward a fixed point, which can be identified by calculating the overall likelihood that the data came from this dataset, given the values for all parameters. However, it will never actually get to that point. This likelihood can be calculated by multiplying the probabilities of the individual observation i:

$$\prod_i (p_A \Pr[x_i \mid A] + p_B \Pr[x_i \mid B])$$

Where the probabilities given the cluster A and B are determined from the normal distribution function $f(x; \mu, \sigma)$ (Witten et al, 2005). The likelihood is a measurement of the goodness of the clustering process. This number should be increased after each iteration.

3.8 Results

Though the most commonly used techniques for exploratory data analysis are a multitude of statistical methods and in particular graphical displays, cluster analysis can also be used for EDA. As earlier discussed, cluster analysis is a technique that can be used for finding the common characteristics in a data set. Understanding the characteristics of a data set can assist the user in making sense of the data. There are many possible uses for this technique including developing specific strategies, policy, anomaly detection techniques, etc.

Using the four original attributes, LANVFCDFUNC, LANVFCDORLC, LANVFINRESP, and LANCDEVENNEGO with the EM algorithm for conceptual clustering creates three clusters. The result is shown in Figure 3.5. From using the four original attributes, 99% (49,199) of transactions are grouped into the same cluster, cluster0. Only 223 and 117 transactions are grouped into cluster1 and cluster2. When observing the original dataset, it becomes clear that cluster1 and cluster2 are transactions of which comments are manually entered. Though the reason given for those transactions are varied, the nature of the comment is the same, they are manual comments. They could have been entered manually partially or completely.

Figure 3.6 shows that when the four original attributes are used as the clustering attributes, this data set can be grouped to a set of meaningful clusters. Dots with the same color are the transactions in the same cluster. The more homogeneous the colors in the group are; the clearer or better the clustering results appear to be.

```
=== Run information ===
Scheme:       weka.clusterers.EM -I 100 -N -1 -M 1.0E-6 -S 100
Relation:     5738Main
Instances:    49539
Attributes:   7
              LANVFCDFUNC
              LANVFCDORLC
              LANVFINRESP
              LANVFCDSTPR
              LANCDEVENNEGO
Test mode:    evaluate on training data
=== Model and evaluation on training set ===
EM
==
Number of clusters selected by cross validation: 3
Cluster
Attribute                      0          1          2
                          (0.99)          0          0
LANVFCDFUNC
  mean                         0  1124089.5          0
  std.dev.              75255.23   13675.25     3.4191

LANVFCDORLC
  mean                        41    11.0179    17.2051
  std.dev.                2.3463     0.2673     8.1624

LANVFINRESP
  U                        49200        224        115
  A                            1          1          4
  [total]                  49201        225        119
LANVFCDSTPR
  mean                         1          1     0.9487
  std.dev.                 0.011      0.011     0.2206

LANCDEVENNEGO
  mean                       603    606.6251  2130.9904
  std.dev.              327.8754          0  6571.7138

Clustered Instances
0      49199 ( 99%)
1        223 (  0%)
2        117 (  0%)
Log likelihood: -16.99899
```

Figure 3.5: Clustering Result from using the four remaining attributes

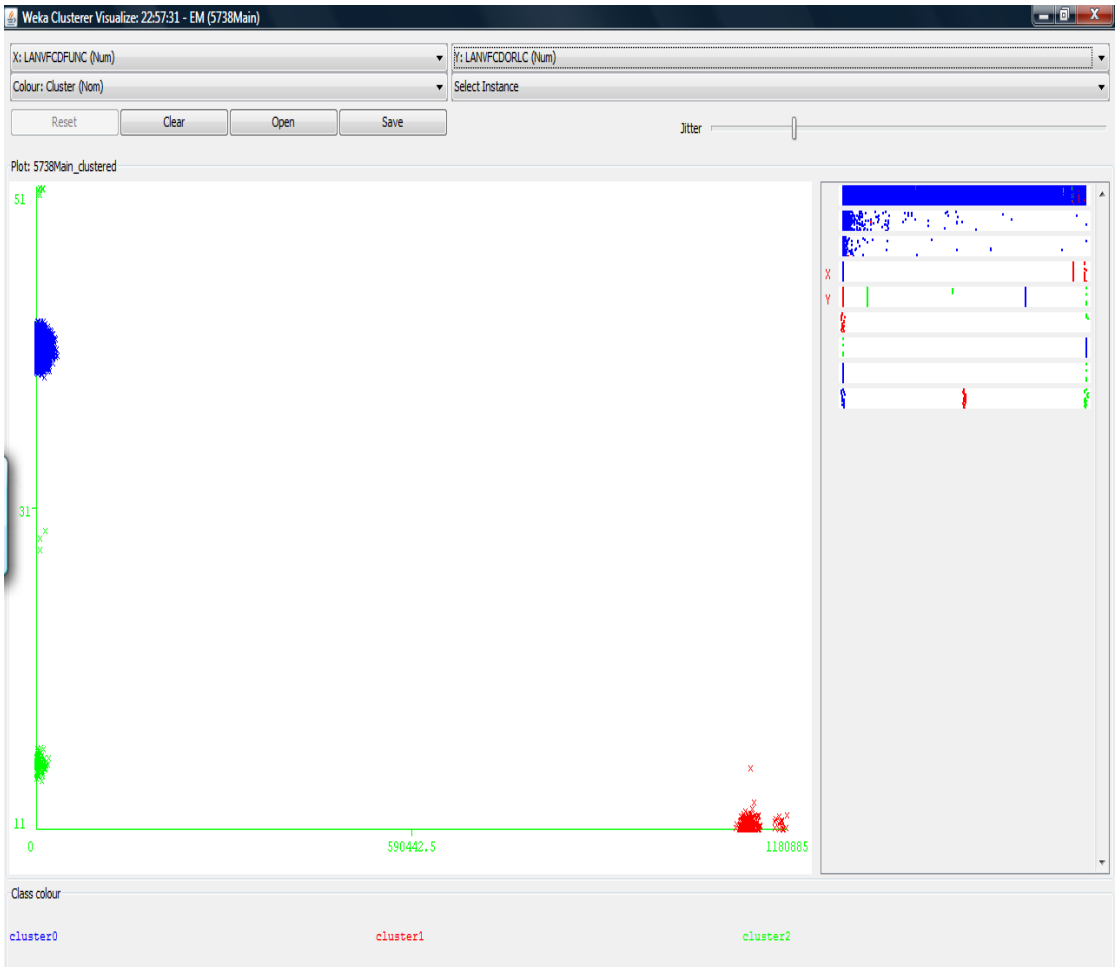

Figure 3.6 Visualization of Clustering Results (`LANVFCDFUNC` and `LANVFCDORLC`)

Though the resulting cluster is clear (i.e. unseen observations can be classified into groups easily) and meaningful, it may not necessarily be useful. For example, in this clustering result, it is possible to tell which transactions are manually entered. Whether the knowledge about the nature of the transaction is useful is an important question to consider.

When using open comment attribute with the EM algorithm, seven clusters are created. Dominant characteristics or the content of the comment in each cluster are summarized in the Table 3.5.

Table 3.5 Content of the Comment Fields in Each Cluster

Cluster No	Content of the comment fields
Cluster0	70 - RESOLUCAO 2025-CLIENTE NAO RECADASTRADO with other message
Cluster1	02 - VALOR LANCTO MAIOR QUE O SALDO with 01902 *TAXA ADMINISTRATIVA OR 02 - VALOR LANCTO MAIOR QUE O SALDO with 06246 *DEB AUT REVISTA SELECOES
Cluster2	01 - CONTA INEXISTENTE with other message
Cluster3	Transaction with the comment that have only one message (in addition to the agencia, conta, and the alphanumeric phase generated from the system)AND the alphanumeric phase generated from the system
Cluster4	50 - LANC.INVALIDO P/PRODUTO HOT-OVER OU COMPROR with other message
Cluster5	71 - LCTO BLOQUEADO P/ CONTA NAO HABILITADA with other message 72 - LCTO BLOQUEADO P/ CONTA PARALISADA with other message
Cluster6	02 - VALOR LANCTO MAIOR QUE O SALDO with other message but NOT 01902 *TAXA ADMINISTRATIVA OR 06246 *DEB AUT REVISTA SELECOES - Transaction with only one message (in addition to AGENCIA and CONTA) WITHOUT alphanumeric phase generated from the system - Transaction that have the massages too varied to parsed

Transactions with similar comments are grouped together. For example, the transaction with the inexistent accounts (01 - CONTA INEXISTENTE) would be in cluster2. There is additional information relating to the inexistent accounts presented in the part4. These clusters represent different reasons that the transactions are transferred to this transitory account. The visualization of the assigned clusters is shown in Figure 3.7 and Figure 3.8. With the limitations of the visualizations in this paper, the attributes and

their relationships can be shown in at most three dimensions; the x-axis, y-axis and the color. Therefore, even though cluster analysis is a multidimensional analysis (i.e. several attributes can be used as the input at the same time), only three dimensions (of the input attributes and the results) can be shown. The assigned clusters are visualized by using color; while other two attributes would be visualized using the x and y axis. The use of color will make the distinction and/or the interpretation of the results easier. By observing dots (or observations) in different colors, the reader would easily understand that they are different groups or clusters.

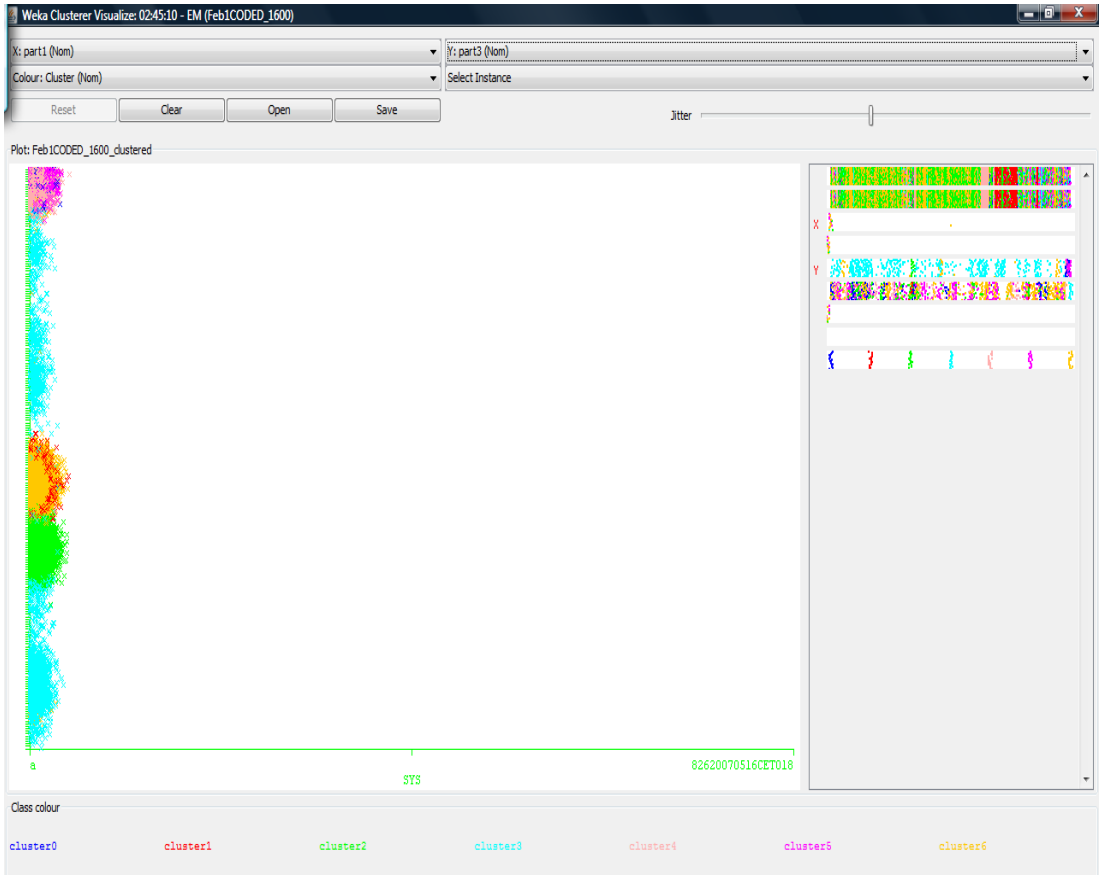

Figure 3.7 Assigned clusters and the value in part1 and part3 of the comment field.

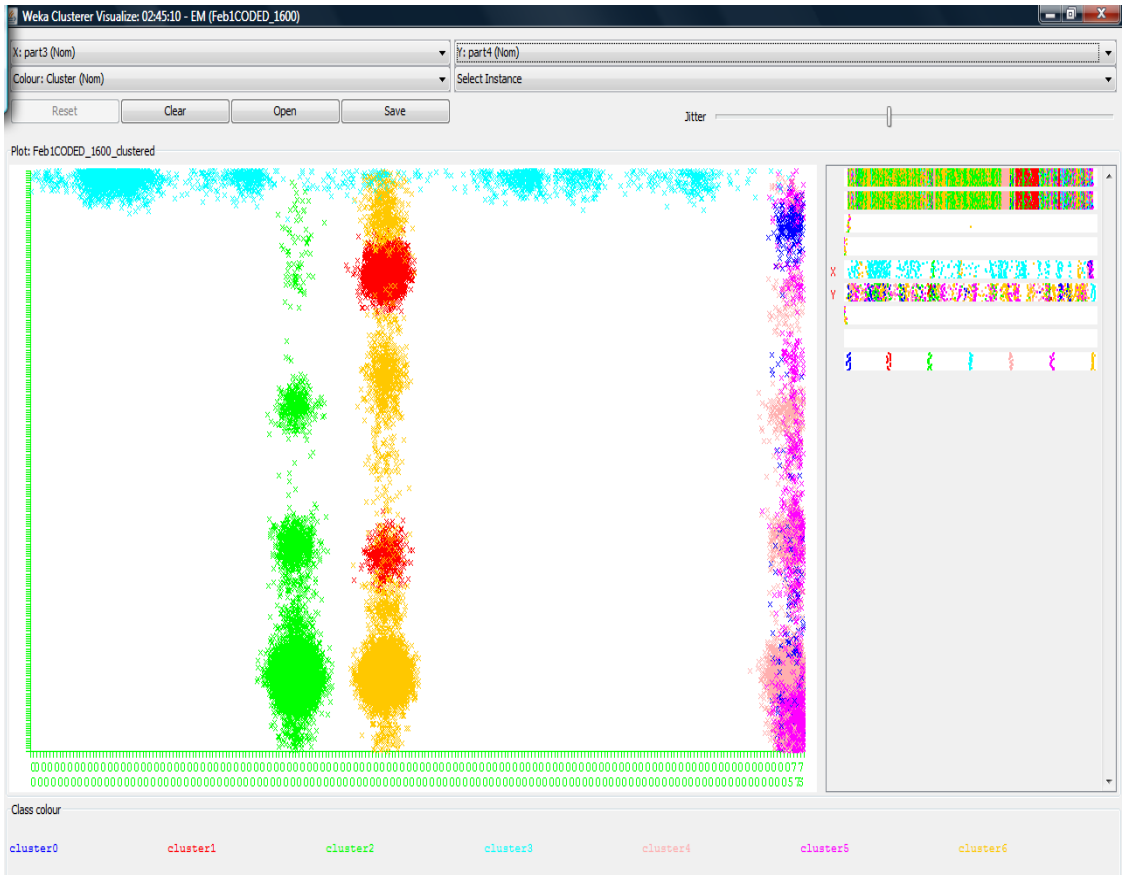

Figure 3.8 Assigned Clusters and the value of part3 and part4 of the comment field(2).

Though the free form comment field has no standardized format, it could be parsed or separated into four parts. Most transactions have the branch (AGENCIA) and account number (CONTA) as the first two parts of the free form comment. The remaining two parts are mainly coded messages (coded number and written message). Because the first two parts of the comment are mostly (but not all) the same, it is justifiable to select part3 and part4 for visualization purposes.

Transactions having similar comments are grouped into the same clusters. From the graphical visualization, it shows that there are clusters. Dots represent individual transactions where the same colors represent the same clusters. Figure 3.8 highlights that the most grouped transactions create large areas of a single color. There are areas for

yellow, green, purple, red, light blue, blue. The x-axis represents part3 of the comment, while y-axis represents part4. The large areas of single color demonstrate that the transactions from the same clusters have the same values in part3 and part4.

Table 3.6 Number of Transactions by Clusters

Cluster name	Number of Transaction	Percentage
cluster0	491	0.99%
cluster1	4010	8.09%
cluster2	19005	38.36%
cluster3	2575	5.20%
cluster4	4277	8.63%
cluster5	3408	6.88%
cluster6	15773	31.84%
Grand Total	49539	100.00%

Numbers of transactions in each cluster are shown in Table 3.6. The majority of transactions (70.20%) are in cluster2 (38.36%) and cluster6 (31.84%). The cluster with the smallest number of transactions is cluster0 (0.99%). The remaining clusters, which are cluster1, clsuter3, cluser4 and cluster5, have 8.09%, 5.20%, 8.63% and 6.88% respectively.

This dataset consists of transactions entered into a single transitory account (account 5738) by over 1,000 branches (AGENCIA) of a major foreign bank. Some branches (AGENCIA) are bigger and originate more transactions than others. The number of transactions by branches ranges from 1 to over 1,500 transactions. The top 20 branches (AGENCIA) in term of number of transactions originated comprise 20% of the total number of transactions in the transitory account number 5738. In order to gain a better understanding of the dataset, the clustering results by branch is examined. The

distribution of the clustered transactions of the top 20 branches (AGENCIA) is examined. It is organized by branch.

Table 3.7 Distribution of the Transaction into Clusters by Top 20 Branches

Branch	cluster0	cluster1	cluster2	cluster3	cluster4	cluster5	cluster6	Total
7227		6	78		1560	5	38	1687
1715			5		1003	1	7	1016
90	5	5	26	2	1	12	954	1005
7246		9	865	1		6	23	904
329		4	324	1			539	868
444		6	48	1		1	470	526
927		457	22			1		480
201		377	51	2	16	9	7	462
379		9	393		7	2		411
130			234	3	3	3	142	385
529	4	6	286	1	1	5	58	361
986		5	48		290	7	8	358
7335		12	183	2			111	308
870		3	277	2		6		288
206			254	6		3	12	275
562		3	239				31	273
811		9	74			3	184	270
351		12	219	9		5	4	249
126			4	233		10	1	248
1693		21	185	2		3	35	246

Table 3.7 shows that different branches have different dominating types of comments. For example, branch 7227, 1715 and 986 originate many transactions which are in cluster4; while branch 90 and 444 originate many transactions which are either 02 - VALOR LANCTO MAIOR QUE O SALDO+ an additional comment, comment with one message, or comment which are impossible to parse. Some branches have originated two dominating type of comments or reasons; for example, branch329, 130, 7335 and 811. These branches have two dominating type of comments or reasons (i.e. 01 - CONTA INEXISTENTE + additional comment AND transactions with incomplete comment).

There can be explanations to why such concentration exists. For example, all branches use the same transitory account for the different types of pending transactions (i.e. account 5738 could be for transactions without account number, while account 60836 could be for transactions with insufficient funds, etc). A transitory account is supposed to be used for the same purpose for all branches.

Examining transactions from a particular transitory account in a particular branch, there should be only one cluster. Transactions from clusters other than the one with the highest population may be considered an anomaly.

From the dataset, there are 1016 transactions generated from branch 1715. These transactions are grouped into cluster2 (5), cluster4 (1003), cluster5 (1) and cluster6 (7). More than 98% of transactions are in cluster4. The remaining transactions (which are 5 transactions from cluster2, 1 transaction from cluster5 and 7 transactions from cluster6) are the minority. Using this rationale to evaluate the clustering results of account 5738, thirteen transactions from branch 1715 can be flagged as possible anomalies. The total number and the percentage of transactions in these remaining groups are so small that they are suspicious of being illegitimate. Though the reasons or explanation related to the transactions may seem valid, the small volume can lead to the doubt of their presences. Further investigation and/or tests are needed to check the legitimacy of the transactions.

Table 3.8 Percentage of Transactions Grouped into Clusters for the Top 20 Branches

Branch	cluster0	cluster1	cluster2	cluster3	cluster4	cluster5	cluster6	Total
7227		0.3557%	4.6236%		92.4718%	0.2964%	2.2525%	100%
1715			0.4921%		98.7205%	0.0984%	0.6890%	100%
90	0.4975%	0.4975%	2.5871%	0.1990%	0.0995%	1.1940%	94.9254%	100%
7246		0.9956%	95.6858%	0.1106%	0.0000%	0.6637%	2.5442%	100%
329		0.4608%	37.3272%	0.1152%			62.0968%	100%
444		1.1407%	9.1255%	0.1901%		0.1901%	89.3536%	100%
927		95.2083%	4.5833%			0.2083%		100%
201		81.6017%	11.0390%	0.4329%	3.4632%	1.9481%	1.5152%	100%
379		2.1898%	95.6204%		1.7032%	0.4866%		100%
130			60.7792%	0.7792%	0.7792%	0.7792%	36.8831%	100%
529	1.1080%	1.6620%	79.2244%	0.2770%	0.2770%	1.3850%	16.0665%	100%
986		1.3966%	13.4078%		81.0056%	1.9553%	2.2346%	100%
7335		3.8961%	59.4156%	0.6494%			36.0390%	100%
870		1.0417%	96.1806%	0.6944%		2.0833%		100%
206			92.3636%	2.1818%		1.0909%	4.3636%	100%
562		1.0989%	87.5458%				11.3553%	100%
811		3.3333%	27.4074%			1.1111%	68.1481%	100%
351		4.8193%	87.9518%	3.6145%		2.0080%	1.6064%	100%
126			1.6129%	93.9516%		4.0323%	0.4032%	100%
1693		8.5366%	75.2033%	0.8130%		1.2195%	14.2276%	100%

The distributions of transactions grouped into clusters are presented in Table 3.8 and Figure 3.9. The table lists branch and how its transactions are distributed into clusters. Looking at the top 20 branches by the number of transactions indicates that most branches have one or two dominating types of transactions. For example, branch 927 and 201 have over 80% of transactions in cluster1 (02 - VALOR LANCTO MAIOR QUE O SALDO); branch 7246, 379, 529, 870, 206, 562, 351 and 1693 have over 75% of transactions in cluster2 (01 - CONTA INEXISTENTE); branch 126 has over 93% of transactions in cluster3; branch 7227, 1715 and 986 have over 80% of transactions in cluster4(50 - LANC.INVALIDO P/PRODUTO HOT-OVER OU COMPROR); branch 90 and 444 have over 89% of transactions in cluster6 (incomplete comment). There is no branch in the top 20 group that originates the majority of the transaction in cluster0 (70 - RESOLUCAO 2025-CLIENTE NAO RECADASTRADO) and cluster5 (71 - LCTO

BLOQUEADO P/ CONTA NAO HABILITADA; 72 - LCTO BLOQUEADO P/ CONTA PARALISADA). From this knowledge, it is possible to write a program to detect if the incoming transaction does not have similar characteristics as the others.

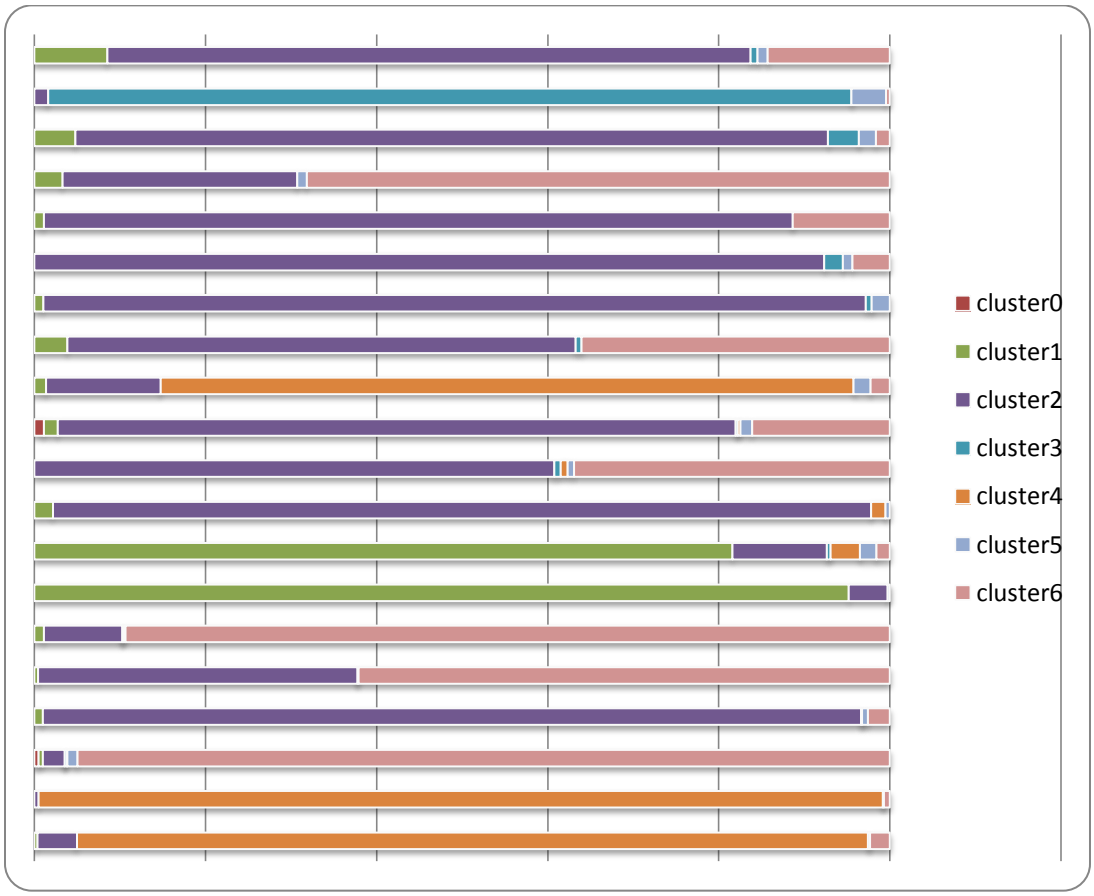

Figure 3.9 Distribution of Transactions into clusters by top 20 branches

Using simple expressions in Perl programming can change the complex fields which is originally impossible to be analyzed into a computable form. After the field is parsed, the patterns and other information can be revealed. Data mining on this data can then be performed.

Cluster Analysis can be used for the exploratory data analysis. At the first glance, it might appear as if the simple counting can be applied and used for this purpose. For

example, transactions with the phrase “70 - RESOLUCAO 2025-CLIENTE NAO RECADASTRADO” can be grouped into cluster1, transactions with the phrase “50 - LANC.INVALIDO P/PRODUTO HOT-OVER OU COMPROR” can be grouped into cluster4. However, cluster analysis is able to group the transactions with similar mistakes into the same groups in such a way that a simple counting of frequency distribution cannot. It incorporates more than one attribute in the consideration of grouping.

For example, transactions with the message “02 - VALOR LANCTO MAIOR QUE O SALDO” are grouped into 2 separated groups by cluster analysis. First group of 02 - VALOR LANCTO MAIOR QUE O SALDO transactions are in cluster1; while the second group are in cluster6. The difference between the two (2) clusters is that cluster1 represents 02 - VALOR LANCTO MAIOR QUE O SALDO with either 01902 *TAXA ADMINISTRATIVA or 06246 *DEB AUT REVISTA SELECOES as the second part of the comment; while 02 - VALOR LANCTO MAIOR QUE O SALDO transaction in cluster6 does not have either 01902 *TAXA ADMINISTRATIVA or 06246 *DEB AUT REVISTA SELECOES. Moreover, some 02 - VALOR LANCTO MAIOR QUE O SALDO transactions which are grouped into cluster6, represent the transaction where the first phase of the comment was entered as 02 - VALOR LANCTO MAIOR QUE O SALDO and the additional information (or 2^{nd} phrase) is missing. If the 02 - VALOR LANCTO MAIOR QUE O SALDO transactions have either 01902 *TAXA ADMINISTRATIVA or 06246 *DEB AUT REVISTA SELECOES as the second (2^{nd}) phrase, they will be grouped into cluster1.

Though the results from clustering using the four original attributes and using the parsed comments are not equivalent, there are some points that should be noted. Firstly,

clustering using the four original attributes can generate three clusters, two of which are a subset of cluster results from the parsed comment. Transactions which are grouped in cluster1 and cluster2 from using four original attributes are grouped into cluster6 from using parsed comment field. Secondly, most transactions (99%) are grouped into cluster0 when four original attributes are used despite the fact that the transactions are of a different nature. Therefore, it might be worth noting that the open comment attribute once parsed can be a very useful variable for conceptual clustering.

3.9 Conclusions

Cluster analysis is used extensively in marketing as a technique to discover market segments. In this aspect, it is used to discover hidden patterns and structures such as market segments. The end benefits depend on the objective of the clustering. For example, after identifying market segments, a marketer may use the information to develop marketing strategies to serve some specific market segments or develop several strategies targeted for each individual segment. Without prior knowledge about the dataset, cluster analysis may be used as a tool to help discover some hidden information.

Using the real dataset from an international bank, this study provides the illustration on how cluster analysis may be applied by auditors to gain knowledge about a dataset. This dataset consists of transactions that are posted onto transitory accounts. These transactions cannot be completed at the time they are entered into the system. The transactions are transferred or posted to transitory accounts temporarily before employees can find the solution to the problem. Once the issue is resolved, the transaction is cleared leaving the ending balance of the transaction as zero. There is very little information relating to the nature of these transitory accounts. Therefore, cluster analysis is an

excellent method for exploring this type of dataset. The clustering technique Expectation Maximization (EM) is performed, resulting in seven clusters. The resulting clusters may be considered as major sub-groups. As a result, better understanding about the dataset may be developed and this knowledge may be useful in the audit planning process.

Cluster analysis is a useful technique for exploratory data analysis. Using a real dataset from a company, the EM technique is applied and major sub-groups of transactions are discovered. The end benefits of the cluster analysis depend on the objective of the clustering and how the resulting clusters are used.

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Chapter 4 Cluster Analysis for Anomaly Detection

4.1 Introduction

Cluster Analysis is a very popular technique used in marketing for the purpose of market segmentation (Erdogan et al, 2006, Lim et al, 2006, Morwitz et al, 1992, Shih et al, 2003). It could be used to group the data such as customers and/or products into groups or segments in order to develop marketing strategies specifically to each segment, for example. In addition to grouping, cluster analysis is used for outlier identification. Outliers can be a by-product of cluster analysis (Agrawal et al, 1998, Aggarwal et al, 1999). Even though clustering and anomaly detection appear to be fundamentally different, several clustering based anomaly detection techniques have been developed in the literature (Chandola et al, 2009).

This study uses data of a major insurance company. It aims at developing a continuous audit or automatic fraud detection process for its electronic wire transfer system. The company would like to develop the monitoring process for the wire payments transferred within and out of the company's system. Funds have been transferred continuously to and from many divisions or business unit. The frequency and volume of the transferred funds are significant in business operations. Several controls are implemented in the systems; for example, requiring several approvers for transactions, setting fund limits for approvers and initiators of the transactions, setting specific bank account for specific type of transactions, etc. The process of the wire transfers is not extremely complicated; however, its high volume has significant impact on business operations. Therefore, depending on only good controls may not be sufficient. With the business world growing more complicated with time, having good

controls in place may not be enough. As a result, management is hoping to find a more effective, innovative, and up-to-date method to monitor the wire transfers.

The objective of this study is to examine the use of cluster analysis as an alternative and innovative anomaly detection technique in the wire transfer system. Several clustering techniques are applied to detect possible anomalous wire transfers. The results are compared and evaluated in terms of understanding the type of possible outcome cluster analysis delivers as well as how it can be used by internal auditors. This study provides a guideline for the usage of this technology in auditing process.

4.2 Anomaly Detection

Outliers are observations that deviate significantly from other observations to the point that they arouse suspicion that they were generated by a different mechanism (Hawkins, 1980). Anomalies occur for many reasons, for example, different classes of data, natural variation in the data and data measurement, and collection error (Tan et al, 2006).

Chandola et al (2009) suggest that anomalies can be classified into three categories: point anomaly, contextual anomaly, and collective anomaly. Point anomaly is a simple form of anomaly that identifies an individual data instance as anomalous in respect to the remaining of data. Contextual anomaly occurs when a data instance is anomalous in specific context. For example, a temperature of 35F is considered normal in winter but rather anomalous in summer. Collective anomaly is the case when a collection of related data instances are anomalous. Duan et al (2009) suggest that there is a possibility that many abnormal events have both temporal and spatial locality, which might form small clusters that also need to be deemed as outliers. In other words, not

only single points but also small clusters can probably be considered as outliers. This type of outlier is called a "cluster-based outlier".

Anomaly detection is the task of identifying observations whose characteristics are significantly different from the rest of the data (Tan et al, 2006). These observations are called outliers or anomalies because they have attribute values that deviate significantly from the expected or typical attribute values. Application of anomaly detection includes fraud detection, credit card fraud detection, network intrusion, etc. Regardless of the applied domain, anomaly detection generally involves three basic steps; 1) identify normality by calculating the "signature" of the data, 2) determine the metric to calculate an observation's degree of deviation from the signature, and 3) set some criteria/threshold to identify anomalous observations which metric measurements are higher than the threshold (Davidson, 2000). A variety of methods for each step have been used in various applications in all fields.

Chondala et al (2009) suggest that with respect to the extent to which the labels are available, anomaly detection techniques can operate in one of three modes: supervised anomaly detection, semi-supervised anomaly detection and unsupervised anomaly detection. Supervised anomaly detection assumes the availability of a training data set which has instances labeled as normal as well as anomaly classes. Semi-supervised anomaly detection assumes that the training data set has labeled instances for only the normal classes. A model corresponding to the normal behavior will be build and used for identifying the anomalous instances in the test data. Unsupervised anomaly detection does not require training data set. It assumes that anomalous instances are far less than the normal instances.

4.3 Cluster Analysis for Anomaly Detection

Chandola et al (2009) propose that clustering based techniques can be grouped into three categories. The first group relies on the assumption that normal data instances belong to a cluster in the data while anomalies do not belong to any cluster(Chandola et al (2009); for example, DBSCAN - Density-Based Spatial Clustering of Applications with Noise (Ester et al, 1996), ROCK-Robust Clustering using links (Guha et al, 2000), SNN cluster - Shared Nearest Neighbor Clustering (Ertoz et al, 2003), FindOut algorithm (Yu et al, 2002) and WaveCluster algorithm (Sheik-Holeslami et al, 1998). Basically these techniques apply a clustering algorithm to the data set and declare any data instances that do not belong to any cluster as anomalous.

The second group relies on the assumption that normal data instances lie close to their closest cluster centroid while anomalies are far away from their closest cluster centroid (Chandola et al, 2009). Self-Organizing Maps (SOM) introduced by Kohonen (1997) is widely used for anomaly detection in many different applications; for example, fraud detection in automobile bodily injury insurance claims (Brockett et al, 1998) and network intrusion detection (Labib et al, 2002, Smith et al, 2002, Ramadas et al, 2003).The techniques in this group basically involve two steps; firstly, grouping data into clusters and secondly calculating distances from cluster centroid to identify anomaly scores.

The third group relies on the assumption that normal data instances belong to large and dense clusters, while anomalies either belong to small or sparse clusters (Chandola et al, 2009). He et al (2003) propose a technique called FindCBLOF to find

size of the cluster to which the data instance belongs and the distance of the data instance to its cluster centroid. These two values make up the score called Cluster-Based Local Outlier Factor (CBLOF). Applying the technique to detect anomalies in astronomical data, Chaudhary et al (2002) propose an anomaly detection model using k-d trees providing partitions of data in linear time. Sun et al (2004) propose a technique called CD-trees. Both techniques define sparse clusters as anomalies; in other words, they determine anomalies based on the density and distance from other clusters.

4.4 The Audit Problem

The insurance company is aiming at developing a continuous audit / fraud detection process. Therefore, the internal audit team of the company has cooperated with the research team to develop automatic models or methodologies that could be used in parallel with the internal audit process. The wire transfer process is selected for model development because of a number of factors as follows. Firstly, the data is available for the analysis. Secondly, the internal audit team identifies that wire transfer is an important process which involves a large number of transaction in the system. Thirdly, a knowledgeable and competent internal audit team is available to assist in the model building process.

The wire transfer process in the company consists of three stages: initiation, approval and payment. First, users in the line of business initiate or request the payment. The request is then needed to be approved by appropriate approvers. Depending on the type and nature of the wires, some may require more approvers than others. After the request is approved, the payment is then made to the payee. Though wire transfer is a significant process, it does not seem yet to have a very good control set in place. There

are cases where the crucial information is missing such as approvers' identification. Specific controls that exist in the system are, for example, users are assigned to a specific transaction and bank account group; therefore they can conduct a certain type of transaction thru specific bank account groups.

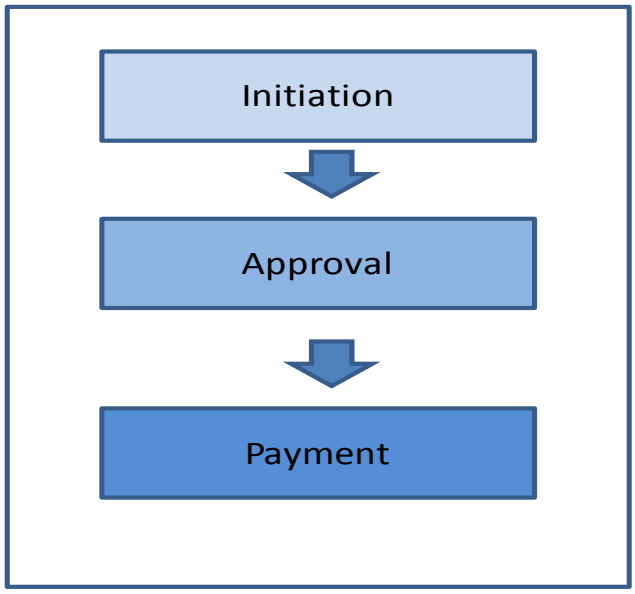

Figure 4.1 Wire Transfer Process

Recognizing the importance of the wire transfer system; the company has been cooperating with an academic institution to create a model for fraud or anomaly identification that can be used along side with their normal internal auditing process. Several indicators are created using statistical methods such as prediction interval test, correlation test and frequency test. For the prediction interval test, the model involves stratifying payees into four categories: 1) payees with one wire payment (P1), 2) payees with two wire payments (P2), 3) payees with three to twenty-nine wire payments (P3), and 4) payees with thirty or more wire payment (P4). Alpha prediction intervals of 90%, 95% and 99% are created to identify outliers. With the statistical nature of these indicators, numbers of transactions are of great concern. For payees with thirty or more

wires (P4), calculating alpha prediction intervals is not an issue. For payees with only one wire payment (P1), a prediction interval can be estimated by grouping them with other payees who also have only one wire payment and calculating the value as a whole. There exist difficulties at this stage dealing with payees who have only two wire payments (P2) and those with three to twenty nine payments (P3). The former group has more than one wire payment, making it impossible to be added to the combined pool with payees that has only one payment. The latter group with three to twenty nine payments does not have the required number of transactions for statistical tests. Therefore, the company is looking for the other alternative methods for detecting outliers for this group of wire transfers.

The company does not seem to have available the record of previously identified frauds or anomalies. However, lacking of such a record does not necessarily mean that there is no fraud in the wire transfer process. Due to the lack of previous fraud history for model development process, applying an unsupervised method is appropriate. The objective of this research is to create an unsupervised model for potential anomaly detection in wire transfer system. The results from the model, which are potential anomalies identified, will be investigated further by the internal audit team.

4.5 Data

4.5.1 General Information

The data obtained from an insurance company consists of wire transactions for a period of time from 2008 to 2010. It includes information on each wire transfer such as its approvers, initiators, senders, receivers; the department or group it belongs to; the amount it has transferred; the designated location it will be sent to as well as its other description or information, etc. The attributes are listed in Table 4.1. It is noticeable that

most attributes are mainly for identification purposes (for examples, initiator id, approver id, cost center id, initiator name, account number, routing number). Though they are very informative, they are not useful for classification. Therefore, based on the original attributes list and additional consultation with the internal auditors, attributes that represent characteristics of the wire transfers are created.

While the insurance company provided data for approximately two years in this project, cluster analysis has been done quarterly due to the following reasons: 1) the data size is large enough for the analysis and not too large to be processed for a reasonable amount of time and 2) the analysis corresponds with the quarterly internal audit process. The result will be presented in detail for one quarter.

Table 4.1 Attribute Information

All_wires	Detail Information
ACCTBIZUNIT	The Line of Business that owns the bank account from which the funds are disbursed
AMOUNT	Amount of each wire (stored as negative number)
APPROVER1ID	User (employee) id of (first) approver
APPROVER1LOB	Cost center of (first) approver
APPROVER1NAME	Fullname of (first) approver (includes phone number)
APPROVER2ID	User (employee) id of (second) approver
APPROVER2LOB	Cost center of (second) approver
APPROVER2NAME	Fullname of (second) approver (includes phone number)
COUNTBIZUNIT	The Line of Business that owns the bank account to which the funds are being sent
CURRENCY	Standard currency code of disbursed funds (e.g. USD, MXN, EUR, etc.)
DATASOURCE	Indicates wire source (system)
EFFDATE	Effective date of funds disbursal
INITIATEDDATE	Date the wire was initiated
INITIATORID	User (employee) id of initiator
INITIATORLOB	Cost center of initiator
INITIATORNAME	Fullname of initiator (including phone number)
INTTRANIND	Identifies whether the wire was between 2 MetLife bank accounts
PAYEE	Payee Name
PAYEEACCTNUM	Payee Bank Account
RANDREP	Indicates whether wire is random or repetitive (i.e. source is line number template)
RECORDTYPE	Type of Record??
REPREF	Reference to the Repetitive Wire Template
ROUTINGNUM	ABA, Fed Wire or Swift Code
SOURCEACCTNUM	Bank account from which funds are disbursed
TRANREF	Descriptive information entered along with the wire
TRANTYPE	TWS transaction type assigned to each wire
WIREID	Unique id for each wire transaction

4.5.2 Description and Distribution of Attributes

Attributes Used:

From the original attributes, the attributes selected and/or created are as follows:

WireType: There are four type of wire transfer: random, repetitive, concentration, and batch. The categories are based on the number of payments and on operational

effectiveness and efficiency. These wire transfers have different characteristics. Therefore, it is reasonable to assume that they may have different behaviors. The brief description of different types of wire transfers is given below.

- Random: infrequent wire transfer,
- Repetitive: Regular and repeated wire transfer such as monthly installments, weekly payments and etc,
- Concentration: Transfer between departments such as transfers between different business units and or branches,
- Batch: Batch wire transfer such as transfers which have been entered at various times during the day but have been processed only at the end of the day.

Table 4.2 Number of Wire Transfer by WireType

WireType	Count
Bat	7495
Ran	1594
Rep	358
Grand Total	**9447**

Payee: Type of payee (Individual who receives wire transfers)

Payees are categorized by the number of payment that he or she received throughout the period. Payees are stratified into four categories:

- P1: if the payee receives only one payment;
- P2 : if the payee receives two payments;
- P3: if the payee receives from three to twenty-nine payment;
- P4: if the payee receives thirty or more.

The objective of this study is to find an alternative method for anomaly detection that could be applied to wire transfer when the types of payee are P2 and P3, in other words, when the payee receives between two to twenty-nine payments. Therefore, among the originally stratified four payee categories, the values of this attribute that appears in this dataset will be only P2 and P3.

The payees are categorized based on the number of payment received due to statistical reasons mentioned in the previous section (The Audit Problem). It is also reasonable to assume that payees from different groups may have different characteristics and/or different behaviors. In order to derive statistical values such as means, median and etc, of a group of values, it is conventional belief that at least 30 observations are needed (Kutner et al, 2004). Therefore, payees who receive 30 or more payments are grouped into P4; while payees who receive less 30 payments are classified into 3 groups based on the number of payments.

Table 4.3 Number of Wire Transfers by Payee

Patron	Count
P2	888
P3	8559
Grand Total	**9447**

Ini: Type of Initiator (Individual who initiates wire transfers)

Type of Initiator is identified by the number of wire transfer he or she initiates throughout the period. Initiator is stratified to four categories:

- I1: if the initiator initiates only one wire transfer;
- I2 : If the initiator initiates two wire transfers;

- I3: If the initiator initiates from three to twenty-nine wire transfers;
- I4: If the initiator initiates thirty or more wire transfers.

The ***Initiators*** are categorized based on the number of payment they have initiated due to statistical factors similar to ***Payee*** categorization.

Table 4.4 Number of Wire Transfer by Initiator

Ini	Count
I1	1
I2	1
I3	80
I4	9365
Grand Total	**9447**

App: Type of Approver (Individual who approves wire transfers);

Type of Approver is identified by the number of wire transfer he or she approves throughout the period. Approvers are stratified to four categories:

- A1: if the approver approves only one wire transfer;
- A2 : If the approver approves two wire transfers;
- A3: If the approver approves from three to twenty-nine wire transfers;
- A4: If the approver approves thirty or more wire transfers.

The similar rationale is applied in the categorization of the ***Approval*** as in the categorization of the ***Payee***.

Table 4.5 Number of Wire Transfer by Approver

App	Count
A3	71
A4	9376
Grand Total	**9447**

Trantype: This attribute provide information on the type of wire transfer. It appears to comprise two pieces of information (phrases or parts). For example, "WIRRAN" is possibly composed of "WIRE" and "RANDOM"; "GTIAUD" is possibly composed of "GTI" and "AUD" (Australian dollar). Therefore, this attribute is parsed into 2 separate parts to reveal more detailed information on the transfers.

This attributed is parsed into 2 parts (P1 and P2).

The first part is P1; while the second part is P2

Table 4.6 Number of Wire Transfer by Trantype

P1	P2	COUNT
ACH	REP	72
ACH	REPTXP	5
CM	WIRE	4
GTI	AUD	6
GTI	CAD	20
GTI	CHF	3
GTI	EUR	13
GTI	GBP	22
GTI	JPY	15
GTI	MXN	7
GTI	NZD	4
GTI	PLN	4
GTI	SEK	6
GTI	USD	1
GTR	AUDFXC	4
GTR	CADFXC	11
GTR	CHFFXC	3
GTR	EURFXC	5
GTR	GBPFXC	7
GTR	JPYFXC	2
GTR	MXNFXC	1
GTR	NOKFXC	1
GTR	PLNFXC	3
GTR	SEKFXC	3
GTR	TRYFXC	2
GTS	CHF	5
GTS	GBP	3
GTS	NOK	1
GTS	PLN	2
GTS	USD	2

P1	P2	COUNT
INTERCO	SWT	5
INTERCO	(blank)	2
INTRACO	REP	11
INTRACO	(blank)	9
IRE	EURSEM	1
IRE	GBP	1
IRE	GBPSEM	5
UK	GBP	1
UK	GBPSEM	37
WIR	AGLN	113
WIR	RAN	7223
WIR	RANAP	4
WIR	RANARM	28
WIR	RAND	7
WIR	RANEVB	711
WIR	RANM	179
WIR	REP	233
WIR	REPARM	5
WIR	RSWTO	5
WIR	SEM	74
WIR	SEMAG	5
WIR	SEMARM	3
WIR	SWT	113
WIR	SWTAP	8
WIRE	SWT	18
WIRE	(blank)	409
Grand Total		**9447**

COSTCTR: Cost center is the relationship between the initiator and approvers of the wire transfers. Cost center provides information related to the group or center that the specific employee belongs to for cost management purposes. Different cost center represents different branches or different business lines, etc. There are three different

types of cost center information in this dataset: 1) Initiators' cost center, 2) Approver1's cost center, and 3) Approver2's cost center. Depending on the transaction type, there should be different relationship between Initiator's cost center and Approvers' cost center. This attribute is created to represent the relationship between initiators and approvers. It shows how close they are (i.e. if they are from the same cost center, etc). The cost center relationship can be grouped into eleven categories:

When cost center information is not available

- A: InitiatorLOB = "" AND Approver1LOB = "" AND Approver2LOB = "" then COSTCTR="A" – Information on cost center of Initiator, Approver1 and Approver2 is not available.

When cost center information is available for initiator and approver1

(Only one approver needed for the transaction)

- ((InitiatorLOB = Approver1LOB) AND (Approver2LOB="")) then COSTCTR="C" – Initiator and Approver1 are from the same cost center but the information on cost center of Approver2 is not available.
- ((InitiatorLOB <> Approver1LOB) AND (Approver2LOB="")) then COSTCTR="D" – Initiator and Approver1 are NOT from the same cost center but the information on cost center of Approver2 is not available.

When cost center information is available for initiator, approver1 and approver2

- InitiatorLOB = Approver1LOB =Approver2LOB then COSTCTR="B" – Initiator, Approver1 and Approver2 are from the same cost center.
- ((InitiatorLOB <> Approver1LOB) AND (Approver2LOB <>"") AND (InitiatorLOB <> Approver2LOB) AND (Approver1LOB <>Approver2LOB)) then COSTCTR="E" – Initiator and Approver1 are NOT from the same cost center; Initiator and Approver2 are NOT from the same cost center.
- ((InitiatorLOB <> Approver1LOB) AND (Approver2LOB <>"") AND (InitiatorLOB = Approver2LOB)) then COSTCTR="F"; – Initiator and Approver1 are NOT from the same cost center; Initiator and Approver2 are from the same cost center.
- ((InitiatorLOB = Approver1LOB) AND (Approver2LOB <>"") AND (InitiatorLOB <>Approver2LOB)) then COSTCTR="G"; – Initiator and Approver1 are from the same cost center; Initiator and Approver2 are NOT from the same cost center.
- ((InitiatorLOB <>Approver1LOB) AND (Approver2LOB =Approver1LOB) AND (InitiatorLOB <> Approver2LOB)) then COSTCTR="H"; – Initiator are NOT from the same cost center as Approver1 and Approver2; however, Approver1 and Approver2 are from the same cost center.

When cost center information is available for approver1 and approval2

- ((InitiatorLOB = "") AND (Approver1LOB=Approver2LOB)) then COSTCTR="I"; – The information of initiator's cost center is not available. Approver1 and Approver 2 are from the same cost center.
- ((InitiatorLOB = "") AND (Approver1LOB <> Approver2LOB)) then COSTCTR="J"; – The information of initiator's cost center is not available. Approver1 and Approver 2 are NOT from the same cost center.

  When cost center information is available only for initiator
- K. ((InitiatorLOB <> "") AND (Approver1LOB = "") AND (Approver2LOB = "") then COSTCTR="K" – Information on cost center is only available for Initiator.

Table 4.7 Number of Wire Transfers by COSTCTR

COSTCTR	Count
A	0
B	7149
C	279
D	232
E	757
F	98
G	214
H	497
I	220
J	1
Grand Total	**9447**

AutoIni : This attribute indicates whether the initiator is an automatic system or a person. It is defined by using the characteristic of the initiator identification. For a regular person, the identification would be numbers. An identification of an automatic system can be alphanumeric. In addition to the aforementioned two major types of initiators, management level employee appears to be another special type of initiator. High ranking

management occasionally initiates, as well as approves wire transfer. The identification of this group of people is mainly represented by their short names.

- If the Initiator is the automatic system, the AutoIni= ‘Y’.
- If the Initiator is not the automatic system, the AutoIni=’N’.
- If the Initiator is a person but he/she has an ID similar to the automatic system, the AutoIni= ‘O’ (e.g. example of the type of id is “JHNDOE”).

Table 4.8 Number of Wire Transfer by AutoIni

AutoIni	Count
N	2079
Y	7368
Grand Total	**9447**

AutoApp: This attribute indicates whether the approver is an automatic system or a person. It is defined by using the characteristic of the approver identification. For a regular person, the identification would be numbers. An identification of an automatic system can be alphanumeric. In addition to the aforementioned two major types of approver, management level employee appears to be another special type of approver. High ranking management occasionally initiates, as well as approves, wire transfer. The identification of this group of people is mainly represented by their short names.

- If the Approver is the automatic system, the AutoApp= ‘Y’.
- If the Approver is not the automatic system, the AutoApp=’N’.
- If the Approver is a person but he/she has an id similar to the automatic system, the AutoApp= ‘O’ (e.g. The example of the type of id is “JHNDOE”).

Table 4.9 Number of Wire Transfer by AutoApp

AutoApp	Count
N	2811
Y	6636
Grand Total	**9447**

NApp: This attribute provide information on the number of approvers for each wire transfer. Depending on the nature and type of wire transfer, different number of approvers is needed. It is reasonable to assume that the higher the risk of wire transfer transaction is, the larger number of approvers is required.

Table 4.10 Number of Wire Transfer by Number of Approvers

NApp	Count
1	511
2	8936
Grand Total	**9447**

4.6 Methodology

4.6.1 Clustering Procedure

Since neither the distribution of the input variables nor other necessary parameters for cluster analysis is known, the EM algorithm is adopted for clustering (Witten et al, 2005). The EM algorithm, or expectation-maximization, involves two steps; 1) "expectation" is the calculation of the cluster probabilities, and 2) "maximization" of the likelihood of the distribution given the data. For this method, only the cluster probabilities, not the cluster themselves, are known for each observation. They could be considered as weights. Witten et al (2005) states if w_i is the probability that observation i belongs to cluster A, the mean and standard deviation for cluster A are

$$\mu_A = \frac{w_1 x_1 + w_2 x_2 + ... + w_n x_n}{w_1 + w_2 + ... + w_n}$$

$$\sigma_A^2 = \frac{w_1 (x_1 - \mu)^2 + w_2 (x_2 - \mu)^2 + ... + w_n (x_n - \mu)^2}{w_1 + w_2 + ... + w_n}$$

The EM algorithm converges toward a fixed point which can be identified by calculating the overall likelihood of the data being in this dataset, given the values of all parameters. However, it will never reach that exact point. This likelihood can be calculated by multiplying the probabilities of individual observation i:

$$\prod_i (p_A \Pr[x_i \mid A] + p_B \Pr[x_i \mid B])$$

Where the probabilities given the cluster A and B are determined by the normal distribution function $f(x; \mu, \sigma)$ (Witten et al, 2005). Likelihood is a measurement of the goodness of the clustering process. This number should be increased along the iteration process.

4.6.2 Anomaly Detection

How to define an outlier or anomaly is considered a controversial issue in research. Different research questions and domain knowledge can lead to different definitions of what an outlier or anomalous observation is. When dealing with data with continuous values and a normal distribution, an outlier could be values which are two (2) standard deviations above and below the mean values (MEAN ±2STD). When data are categorical, however, defining values above or below the mean would be impossible.

In the wire transfer dataset, most data are categorical. The clustering procedure was done using the combination of categorical and numeric attributes. In order to identify anomalous activities in the wire transfer dataset, four identification methods are used.

First Method: DBSCAN

The first method of detection is based on the assumption that normal data instances belong to a cluster in the data; while anomalies do not belong to any cluster. There are several clustering techniques that can be classified into this group. In this research, however, DBSCAN proposed by Ester et al (1996) is used because of its availability in the software selected.

DBSCAN stands for **D**ensity-**B**ased **S**patial **C**lustering of **A**pplications with **N**oise (Ester et al, 1996). It is a type of density-based clustering and does not require an input of the number of clusters in the analysis. Moreover, it can find arbitrarily shaped clusters. Because it also has a notion of noise, it can also be used for anomaly detection..

DBSCAN requires two parameters: ε (Eps) and the minimum number of points required to form a cluster (minPts). It starts with an arbitrary starting point. Then points in its ε-neighborhood are retrieved. Once it contains sufficient points, a cluster is formed. Otherwise, the point is labeled as noise. A point is a core point if it has more than a specified number of points (minPts) within ε (Eps); while a border point has fewer than minPts within Eps, it is still in the neighborhood of a core point. Figure 4.2 illustrates the concept of core point, border point and noise. When the parameters are Eps=1 and minPts=5, point A is a core point. On the other hand, point B is a border point because it does not have enough points in its neighborhood to be a core point but it is located in the core point's neighborhood. Point C is noise as shown in Figure 4.2.

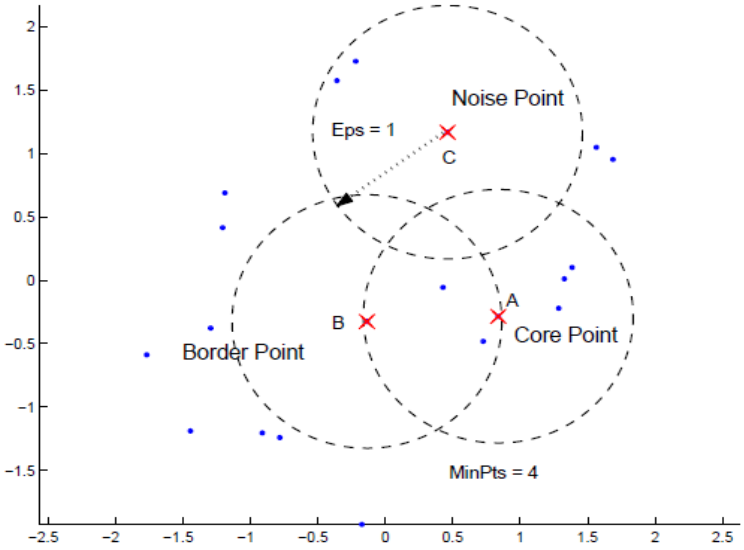

Figure 4.2 Illustration of Core Point, Border Point and Noise (Tan et al, 2011)

Any two core points that are close to an extent within a distance *Eps* of one another are considered in the same cluster. A noise point is any point that is neither a core point nor a border point. Noise points are usually discarded. The point originally found as noise might later be found in sufficiently sized ε-environment of a different point. Therefore, it can become part of the cluster.

Algorithm 6.7 DBSCAN Algorithm.

```
1: Initialization: Label all points as noise points and as belonging to no cluster.
   {First find core, border and noise points.}
2: for i = 1 to n (the number of points) do
3:    Find all points within a distance EPS of the i^th point
      (These points, plus the i^th point itself, are the Eps-neighborhood of the point.)
4:    if the number of points in the Eps-neighborhood ≥ MinPts then
5:       Label the i^th point as a core point
6:       for all points in the Eps-neighborhood, except i^th the point itself do
7:          if the point is still labelled as a noise point then
8:             Label the point as a border point
9:          end if
10:      end for
11:   end if
12: end for
   {Then we find the clusters.}
13: Eliminate noise points
14: current_cluster_label ← 1
15: for all core points do
16:   if the core point has no cluster label then
17:      current_cluster_label ← current_cluster_label + 1
18:      Label the current core point with cluster label current_cluster_label
19:   end if
20:   for all points in the Eps-neighborhood, except i^th the point itself do
21:      if the point does not have a cluster label then
22:         Label the point with cluster label current_cluster_label
23:      end if
24:   end for
25: end for
```

Figure 4.3 DBSC AN Algorithm (Tan et al, 2011)

Because of the notion of noise, DBSCAN has been used for anomaly detection. Observations which cannot be grouped into any cluster are identified as noise or possible anomalies.

Second Method: Distance-Based Outliers

They are individual wires (observations) which are far/different from other wires (observations) in the same cluster. This individual wire is identified using WEKA filtering procedure called "Clustermembership." The procedure calculates the probability of the observations belonging to each cluster. If the probability of the wire belonging in the assigned cluster is less than 0.6, it would be flagged as a possible outlier. The example of the probability calculated and presented by the filtering procedure "Clustermembership" is shown in Table 4.11.

Table 4.11 Probability of an Observation Belonging to Each Cluster, Calculated and Presented by WEKA Filtering Procedure, "Clustermembership"

CLM_ID	Cluster0	Cluster1	Cluster2	Cluster3
20808005145	0.00021	0.806916	0.000961	0.191913
20808005307	0	0.114174	0.002238	0.883588
20808005512	0.000075	0.973995	0.000095	0.025835
20808007974	0.96161	0.036733	0.000011	0.001646
.....	...	...	...	..

Third Method: Cluster-Based Outliers

Clusters which are populated by less than 2% of the total wire transfers are identified as possible outliers. The percentage is set arbitrarily based upon evaluating the results. For consistency of the evaluation, throughout the study, cluster which comprises of less than 2% of the total population are considered as possible outliers.

Fourth Method: Statistical-Based Outliers

Statistical-based outliers are the wires which amount is more than 2 std. or less than -2 std. away from the mean (of the transfer amount of each cluster). After grouping wires into clusters, the mean, standard deviation, and Z-values of all wire transferred in

each clusters are calculated. If the Z-value of the transfer amount is less than -2 or more than 2, the wire would be identified as possible outlier. The continuous attribute "AMOUNT" which was a part of original set of attributes but not a part of the attributes selected as clustering attributes is used. External variables for which information is available on the cluster members, but which was not used in the clustering procedure could be used for cluster comparison (Ketchigan, 1991). The wire transfers are grouped based on the clustering results. The "AMOUNT" is examined.

Outliers identified from all techniques (which are DBSCAN, distance based, cluster based and statistical based outlier) are examined. Four (4) indicators would be assigned for clustering results. If the wire transfers are identified by 4, 3, 2 or 1 techniques, it would be given a score of 4, 3, 2 or 1, respectively.

4.7 Results

The first type of anomaly detection technique is based on the assumption that normal observation will be grouped into clusters, while anomalies would be discarded. The first set of the results finds forty nine clusters based on DBSCAN technique. The largest cluster consists of 60.86% of the population. The remaining clusters each comprise between 0% - 10% of the population. Five clusters contain more than 1% but less than 5% of the population (3.12%, 1.65%, 1.69%, 2.23% and 1.03%). Two clusters contain more than 5% but less than 10% of the population (6.02% and 6.02%). DBSCAN considers single observation or point as noise. The algorithm evaluates each individual point as core point, border point or noise. The clustering results show that 341 wire transfers (3.61%) are discarded as noise.

Table 4.12 Number of Wire Transfer in Each Cluster by DBSCAN

Cluster	No of Member	Percentage	Cluster	No of Member	Percentage
0	295	3.1227%	25	22	0.2329%
1	5749	60.8553%	26	89	0.9421%
2	569	6.0231%	27	22	0.2329%
3	569	6.0231%	28	10	0.1059%
4	48	0.5081%	29	75	0.7939%
5	84	0.8892%	30	19	0.2011%
6	156	1.6513%	31	19	0.2011%
7	37	0.3917%	32	97	1.0268%
8	8	0.0847%	33	33	0.3493%
9	14	0.1482%	34	6	0.0635%
10	57	0.6034%	35	7	0.0741%
11	66	0.6986%	36	25	0.2646%
12	15	0.1588%	37	7	0.0741%
13	44	0.4658%	38	70	0.7410%
14	57	0.6034%	39	9	0.0953%
15	160	1.6937%	40	30	0.3176%
16	89	0.9421%	41	8	0.0847%
17	43	0.4552%	42	9	0.0953%
18	27	0.2858%	43	9	0.0953%
19	211	2.2335%	44	7	0.0741%
20	25	0.2646%	45	24	0.2540%
21	6	0.0635%	46	8	0.0847%
22	16	0.1694%	47	10	0.1059%
23	30	0.3176%	48	88	0.9315%
24	28	0.2964%	NOISE	341	3.6096%

If this study was based on another different assumption that very small clusters can be identified as possible anomalies then the number of anomaly clusters and wire transfers identified would greatly increase. The disadvantage of applying this assumption is that the findings are neither useful to internal auditors nor cost efficient to investigate manually a large number of observations. Some small clusters can possibly be anomalies

i.e. group of anomalies. The number of wire transfers in each cluster and noise observations are presented in Table 4.12.

Though the noise or possible anomalies as identified by DBSCAN may appear to be reasonable in number, other concerns are raised. As the previously shown DBSCAN results, a large number of clusters are considered as small clusters, such as those populated by less than 2% of the observations. Therefore, DBSCAN clustering is re-examined with a different specification. This specification assumes that a cluster should comprise of at least 2% of the population. Therefore, the minimum size of clusters from DBSCAN is set at 189 observations and no lower (approximately 2% of 9447 observations). Under this assumption, five clusters are formed and more than 20% of the wire transfers are identified as noise. Since the level of the noise or possible anomalies is extremely large, it is unlikely that all identified noise observations are real anomalies.

Table 4.13 Number of Wire Transfer in Each Cluster by DBSCAN 2

Cluster	No of Member	Percentage
0	295	3.12%
1	5750	60.87%
2	569	6.02%
3	569	6.02%
4	211	2.23%
NOISE	2053	21.73%
Total	**9447**	**100.00%**

With no benchmark to compare with, the knowledge of the domain expert, in this case- the internal auditor, is needed to evaluate the results. The expert can provide feedback on whether the flagged transactions are indeed real anomaly, only with

suspicious characteristics but in fact normal, or with suspicious characteristics and worth performing further investigation.

The real interpretation of the results derives from the understanding of the data. The wire transfers which are identified as noise have to be checked to see if they are truly anomalous. Some small clusters may be suspicious. For example, a person can commit fraud or generate a small number of suspicious transactions, in other words, there can be a number of suspicious transactions with similar characteristics.

Other anomaly detection techniques are derived from a single cluster analysis. This clustering technique is different from DBSCAN in the aspect of anomaly detection since identifying anomaly/noise/outlier are not its main purposes. In other words, it does not initially identify some transactions as outliers or noise. After clustering, several anomaly detection techniques are implemented on the initial results. The second, third and forth detection methods are applied to the same clustering result. This part of the research will illustrate how similar and/or different each detection technique will identify wire transfers as anomalous one.

The clustering results of using the Expectation Maximization with the wire transfer for the first quarter of 2010 are presented in Table 4.14. The number of clusters generated by EM clustering is fourteen. Over 60% of the wire transfers are grouped into cluster0. The remaining percentage is distributed among the remaining twelve clusters which includes four clusters with less 1% of the population (cluster1: 0.25%, cluster4: 0.41%, cluster11: 0.05% and cluster13: 0.34%). Five clusters with 1-5% of the populations. These clusters are cluster5: 3.97%, cluster6: 3.40%, cluster7: 1.03%,

cluster8: 4.38%, cluster10: 2.33% and cluster12: 1.12%); and two clusters with more than 5% of the population, cluster2 (8.33%) and cluster9 (7.49%).

Table 4.14 Distribution of Wire Transfer by Clusters

Cluster	Number of wire transfer	Percentage
0	6319	66.89%
1	24	0.25%
2	787	8.33%
4	39	0.41%
5	375	3.97%
6	321	3.40%
7	97	1.03%
8	414	4.38%
9	708	7.49%
10	220	2.33%
11	5	0.05%
12	106	1.12%
13	32	0.34%
Total	**9447**	**100.00%**

The average and standard deviation of the amount of the wire transfer in monetary value is presented in Table 4.15. By examining the average and standard deviation, it can be noticed quite clearly that the amount of the wire transfer fluctuates substantially. The standard deviations are very high. All clusters with an exception of cluster0 have the standard deviations of the amount higher than the average. In many cases, the standard deviations of the amount are more than two to three times of the average of the amount in the same clusters; for example, cluster4, the average is 560,820,174.20, while the standard deviation is 2,048,154,558.56.

Table 4.15 Average and Stand deviation of the Monetary amount of Wire Transfer

	Values	
Row Labels	**Average of amount**	**StdDev of amount**
cluster0	220,404.43	140,586.10
cluster1	5,539,783.70	18,789,154.95
cluster2	1,920,884.98	6,672,814.49
cluster4	560,820,174.20	2,048,154,558.56
cluster5	67,021,229.80	659,558,588.44
cluster6	2,079,378.25	16,959,186.68
cluster7	86,042.74	170,314.74
cluster8	17,401,415.99	270,847,828.01
cluster9	391,898.44	4,840,719.35
cluster10	1,393,105.01	6,988,986.20
cluster11	172,598.29	212,731.04
cluster12	51,913.36	346,500.70
cluster13	2,987,894.22	5,092,731.53
Grand Total	**6,203,907.40**	**196,917,603.81**

In the second detection method, possible anomalies that are identified as clusters are those smaller in size such as having less than 2% of the population as the member of clusters. The clusters, which fell into this category, are Cluster1, Cluster4, Cluster7, Cluster11, Cluster12 and Cluster13 with cluster members as 24(0.25%), 39(0.41%), 97(1.03%), 5(0.05%), 106(1.12%) and 32(0.34%).

In the third detection method, possible anomalies are identified as single wire transfers that have low probabilities of belonging to its assigned clusters. The "Clustermembership" filtering algorithm from WEKA is applied to provide such probabilities. The distribution of the anomalies by clusters as identified by this method is presented in Table 4.16.

Table 4.16 Distribution of Possible Anomalies as Identified by Distance-Based Outliers

Distribution of Possible Anomalies: By Distance -Based Outliers	
Cluster	**Number of Anomalies**
Cluster0	0
Cluster1	0
Cluster2	164
Cluster4	10
Cluster5	9
Cluster6	9
Cluster7	0
Cluster8	0
Cluster9	0
Cluster10	9
Cluster11	2
Cluster12	6
Cluster13	0
Total	**209**

In the fourth method, means and standard deviation of the wire transfer amount of each cluster are calculated. The wire transfers which have the amount above and below 2 standard deviations of the cluster mean are identified as possible anomalies. The results are shown in Table 4.17. It is understandable that in this case the larger cluster will naturally yield many possible anomalies. On the other hand, even though, some clusters are very small, there can also be possible anomalies present; for example, Cluster1, Cluster4, Cluster7, Cluster12 and Cluster13.

Table 4.17 Distribution of Possible Anomalies by Cluster Statistics

Distribution of Possible Anomalies: By Cluster Statistics	
Cluster	**Number of Anomalies**
cluster0	253
cluster1	1
cluster2	29
cluster4	2
cluster5	4
cluster6	1
cluster7	3
cluster8	1
cluster9	2
cluster10	5
cluster11	0
cluster12	2
cluster13	2
Grand Total	305

Based on the clustering procedures selected and anomaly detection specified in the previous section, the comparison of wire transfers flagged as possible anomalies is presented in Table 4.18. This table presents the result of different specifications of the anomalies on a single clustering result. The Expectation Maximization clustering is applied first and the clustering result is then examined. Three different assumptions of anomalies are used to identify some observations as possible anomalies/outliers. The results are shown by clusters.

Table 4.18 Comparison of the Number of Anomalies Identified

	Comparison of Number of Anomalies Identified		
Cluster	**Distance-Based**	**Cluster-Based**	**Cluster Statistics**
cluster0	0	0	253
cluster1	0	24	1
cluster2	164	0	29
cluster4	10	39	2
cluster5	9	0	4
cluster6	9	0	1
cluster7	0	97	3
cluster8	0	0	1
cluster9	0	0	2
cluster10	9	0	5
cluster11	2	5	0
cluster12	6	106	2
cluster13	0	32	2
Grand Total	**209**	**303**	**305**

In addition to Expectation Maximization clustering, DBSCAN clustering is examined as mentioned previously at the beginning of the section. The results of each clustering procedures and the anomaly detection are combined and examined.

From the total of 9,447 wire transfers from quarter one in 2010, there are 927 wire transfers flagged by one technique; 81 wire transfers are flagged by two techniques; and 23 wire transfers are flagged by three techniques. The remaining 8,416 wire transfers are not flagged by any of the method. There is no wire transfer flagged by all four techniques. The result is shown in Table 4.19

Table 4.19 Number of Wire Transfer flagged as possible Anomalies

Result	Number of Wire Transfer
Wire Transfer -Not flagged by any Technique	8416
Wire Transfer -flagged by ONE Technique	927
Wire Transfer - Flagged by TWO Techniques	81
Wire Transfer - Flagged by THREE Techniques	23
Grand Total	**9447**

These flagged wires will be given anomaly scores accordingly. The flagged wire and the assigned anomaly scores will be assigned to the other score set of rule-based detection technique to arrive at the final detection scores. A number of flagged wires will be selected for further investigation to check if they are real anomalies.

The comparison of the results is presented in Table 4.20. Though DBSCAN is a well known technique for anomaly detection, it may not be suitable for this dataset. To get a number of outliers comparable to other techniques, DBSCAN will produce several small clusters. If DBSCAN is set to produce clusters which have comparable sizes to those clusters produced by other clustering techniques, it will identify a large number of observations as outliers. The number of outliers will be too large to be useful for further analysis.

Table 4.20 Outliers Identified by Each Technique

Clustering Technique	Detection Techniques	No. of Outliers
DBSCAN	DBSCAN (Setting minimum number of obserations in each cluster= 6)	322
	DBSCAN (Setting minimum number of observations in each cluster=189)	2053
Expectation Maximization	Distance-based outliers:	209
	Using Clustermembership Filtering (Probability less than 0.6)	
	Cluster-based outliers:	303
	membership less than 2% of population	
	Statistical based outiers:	305
	Amount +/- 2 Standard Deviation	

4.8 Conclusions

This study explores the use of cluster analysis for anomaly detection. Four anomaly detection techniques based on cluster analysis are performed. In addition to the three techniques based on Chandola et al (2009), anomalies based on cluster's statistical values are also presented.

DBSCAN technique is applied to the dataset as the first anomaly detection technique. By applying this technique, 341 wire transfers are identified as noise or possible outliers or possible anomalous transactions. For the remaining detection techniques, Expectation Maximization Algorithm is applied to the dataset to cluster the wire transfers. After wire transfers are clustered, three anomaly detection techniques are then applied to the dataset. Two techniques are based on the remaining two techniques from Chandola et al (2009) and the last technique is based on statistical values.

The second technique assumes that normal data instances belong to large, dense clusters, while anomalies belong to small or sparse clusters (Chandola et al, 2009). For this technique, clusters which with less than 2% of the population are identified as possible anomalous wire transfers.

The third technique assumes that normal data instances lie closer to the nearest cluster centroid (or center) while anomalies are far away from the nearest cluster centroid (Chandola et al, 2009). For this technique, possible anomalies are identified as single wire transfers that have low probabilities of belonging to clusters they are assigned to.

The fourth technique considers the use of statistical values in order to find possible anomalous wire transfers. The wire transfers with the amount above and below 2 standard deviations from the clusters' mean are identified as possible anomalies.

By comparing the results from different detection techniques, the wire transfers flagged by all of the methods are not very similar, i.e. from Table 4.19, only 23 wires transfers are flagged by three methods. There is no wire transfer transaction flagged by all methods. There are many possible explanations. Firstly, on the extremely positive side, there are no real anomalous wire transfers; however, each technique still has to identify something as possible outliers/anomalous transfers. Secondly, the assumption underlying the detection techniques are different. Applying different assumptions, different anomalous wire transfers will be identified. Thirdly, the choices in the model building process can be the main reason. The choice of the clustering technique selection, parameters usage and/or attributes input can have great impact on the outcome. In sum, if different clustering algorithm is selected or different parameters are set, the results can be completely different from the results presented in this research.

Without a labeled dataset, it is very difficult to evaluate the results. It is impossible to justify which technique is the better one. One possible alternative to evaluate the detection technique when a labeled dataset is not available is to use simulation. An experiment can be set up similar to Milligan et al (1985). Under the

assumption that the original dataset is free from error and/or anomalies, synthetic errors may be seeded or added. Each technique will then be evaluated by how well it is able to detect or identify the seeded error. A better technique will be the one that is able to identify the most seeded errors. However, the results should be examined with care. It also depends on the synthetic error generation process that one detection technique is better than the other.

Without either the labeled data or the application of simulation, in order to evaluate if one clustering technique can produce better results than others techniques, the knowledge from domain experts will be required. The experts will use their expertise and knowledge about the subject matters for evaluation. The question of whether one technique is better than others also depends greatly on different usage. One technique may be good / suitable for one purpose but not others.

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Chapter 5 Cluster Analysis and Rule Based Anomaly Detection

5.1 Introduction

Clustering is an unsupervised learning algorithm, which means that there is no label or class for the data (Kachigan, 1991). Clustering is a useful technique for grouping data points such that points within a single group or cluster are similar, while points in different groups are dissimilar. There is no absolute best clustering technique. The most appropriate technique is simply the one that provides the results that are most useful for the user's purposes. Moreover, the cluster evaluation is quite subjective because the results can be interpreted in different ways.

Clustering as an unsupervised learning algorithm is a good candidate for fraud and anomaly detection. Automating fraud filtering can be of great value for continuous audits. I apply cluster analysis to a unique dataset provided by a major insurance company in the United States and examine the cluster-based outliers. Cluster-based outliers help auditors focus their efforts when evaluating group life insurance claims. Claims with similar characteristics have been grouped together and those clusters with small population have been flagged for further investigations. Some dominant characteristics of those clusters are, for example, large beneficiary payment, large interest amount and long time between claim and disbursement.

This study examines the application of cluster analysis in accounting domain. The results provide a guideline and evidence for the potential application of this technique in the field of audit.

5.2 Anomaly and Anomaly Detection

Outliers are observations that deviate so much from other similar observations that they arouse suspicion that they were generated by a different mechanism (Hawkins, 1980). Anomalies occur for many reasons. For example, data may come from different classes, natural variations in data and data measurement, or collection error (Tan et al, 2006).

Chandola et al (2009) suggest that anomalies can be classified into three categories: point anomalies, contextual anomalies, and collective anomalies. A **point anomaly** is the simplest type of anomaly. It is simply an individual data instance which is identified as anomalous in respect to the rest of the data. A **contextual anomaly** is a data instance that is only anomalous in a specific context. For example, a temperature of 35F is considered normal in winter, but anomalous in summer. A **collective anomaly** is an anomalous collection of related data instances. Duan et al (2009) suggest that there is a possibility that many abnormal events have both temporal and spatial locality, which might form small clusters that also need to be deemed as outliers. In other words, not only single points but also small clusters can probably be considered outliers. This type of outlier is called a "cluster-based outlier".

Anomaly detection is the task of identifying observations whose characteristics are significantly different from the rest of the data (Tan et al, 2006). These observations are called outliers or anomalies because they have attribute values that deviate significantly from the expected or typical attribute values. Regardless of the domain, anomaly detection generally involves three basic steps (Davidson, 2000):

1) identify normality by calculating some "signature" of the data,

2) determine some metric to calculate an observation's degree of deviation from the signature, and

3) set some criteria/threshold which, if exceeded by an observation's metric measurement, indicates an anomaly.

A variety of methods or options for each step have been used in various applications in many areas of knowledge.

Chondola et al (2009) suggest that with respect to the extent to which labels are available, anomaly detection techniques can operate in one of three modes: supervised anomaly detection, semi-supervised anomaly detection and unsupervised anomaly detection. **Supervised anomaly detection** assumes the availability of a training data set which has instances labeled as either normal or anomalous. **Semi-supervised** anomaly detection assumes that the training data set has labeled instances for only the normal class. A model corresponding to the normal behavior will be built and used for identifying anomalous instances in the test data. **Unsupervised** anomaly detection does not require a training data set.

5.3 Cluster Analysis for Anomaly Detection

Chandola et al (2009) proposes that clustering based techniques can be grouped into three categories:

The first group relies on the assumption that normal data instances belong to a cluster in the data while anomalies do not belong to any cluster (Chandola et al, 2009); examples include DBSCAN (Ester et al, 1996), ROCK (Guha et al, 2000), SNN cluster (Ertoz et al, 2003), FindOut algorithm (Yu et al, 2002) and WaveCluster algorithm

(Sheik-Holeslami et al, 1998). These techniques apply a clustering algorithm to the data set and declare any data instances that do not belong to any cluster as anomalous.

The second group relies on the assumption that normal data instances lie close to their closest cluster centroid while anomalies are far away from their closest cluster centroid (Chandola et al, 2009). Self-Organizing Maps (SOM) introduced by Kohonen (1997) is widely used to for anomaly detection in many different applications; for example, fraud detection in automobile bodily injury insurance claims (Brockett et al, 1998) and network intrusion detection (Labib et al, 2002, Smith et al, 2002, Ramadas et al, 2003) .The techniques in this group involve two steps; grouping data into clusters, then calculating distances from cluster centroids to develop anomaly scores.

The third group relies on the assumption that normal data instances belong to large and dense clusters, while anomalies belong to either small or sparse clusters (Chandola et al, 2009). He et al (2003) propose a technique called FindCBLOF to find size of the cluster to which the data instance belongs and the distance of the data instance to its cluster centroid. These two values make up the score called Cluster-Based Local Outlier Factor (CBLOF). Applying the technique to detect anomalies in astronomical data, Chaudhary et al (2002) propose an anomaly detection model using k-d trees providing partitions of data in linear time. Sun et al (2004) propose a technique called CD-trees. Both techniques define sparse clusters as anomalies.

Some of these techniques mentioned in this section will be applied to the dataset from a real company. Results will be examined to determine if these detection techniques can identify anomalies in dataset.

5.4 The Audit Problem

This study is related to the group life insurance product offered by a major insurance firm to employees of other companies in the United States. Group life is typically marketed directly to corporations.

Group life insurance differs from individual life insurance in many ways. For example, group life insurance is sold to companies in volume (i.e. Company A buys group life insurance for 100 employees); while individual life insurance is sold individually to the insured (i.e. Mr. A purchases a policy for himself). From the perspective of the insurance provider, the purchasing company is the customer in the former case; while the insured is the customer in the latter. Companies that purchase group life insurance offer the insurance to their employees as part of work benefits. The employees might also have the option to purchase additional life insurance. Because of the differences mentioned, the insurance company manages policies and claims from these two types of life insurance differently. Unlike individual life insurance, group insurance providers will not initially keep the information on a particular insured individual. That information is entered into the system only when a claim is received.

When Company A submits a claim, the insurance provider accepts the information from the company as–is, with little or no verification. For example, if Company A submits a claim for John Doe, the insurance provider will check if John Doe is listed in the Social Security Administration's death file (SSA death file). There is neither further verification on the real existence of that employee in the company nor any other verification.

The type of risk, the description of tests, and the follow-up actions currently performed by internal auditors are presented in Table 5.1. The tests performed are simple,

ineffective, and often vague. Some tests are very vague. For example, there is a review for fictitious insured's name or fictitious beneficiary's name. Internal auditor will check for fictitious names in the claim payment system. However, the definition of "fictitious name" and how the fictitious names are defined is not clear. Internal auditors use personal judgment to identify a name as fictitious one.

Because of the poor data quality as a result of manual inputs, some tests do not give very useful results. For example, the test for improper or incorrect data entry by checking the date related data such as birth date, death date, hiring dates, could yield useless results. Given the wrong dates of birth and death of an individual, the resulting ages could be invalid. For example, there are several cases where an insured age's derived from the calculation ((Death date-Birth date)/365) is one digit (0-9 years old). The result would be inconclusive if the data is for normal life insurance. However, an insured cannot be younger than the legal working age for group life insurance.

Table 5.1 Example of Tests Performed by Internal Auditors

#	Risk	Test Description	Follow-up Actions
1	Duplicate payments are made.	Perform duplicate tests by checking the life claim payment file to see if there was more than one payment for the insured by SSN.	Line of business auditor to review output to ensure the payments are duplicate payments.
2	Duplicate payments are made.	Perform duplicate tests by checking the life claim payment file to see if there was more than one payment for the insured by insured's first and last name.	Line of business auditor to review output to ensure the payments are duplicate payments.
3	Fictitious Insured's name was entered into the claim payment system.	Perform testing by reviewing the insured's names for fictitious names	A claim noted with a factitious insured will have the back-up review and also Accurint will be reviewed.
4	Fictitious Beneficiary's name was entered into the claim system.	Perform testing by reviewing the beneficiary's names for ficticious names	A claim noted with a factitious beneficiary will have the back-up review and also Accurint will be reviewed.
5	Insured does not appear on the SSA Death File.	Compare the insured in the claims file to the SSA administrative death file and look at the insureds that do not appear on the report.	Individuals who do not appear on the report will be reviewed.
6	Insured does not appear on the SSA Death File.	Compare the insured from the last audit to the SSA administrative death file and look at insured that do not appear on the report.	Individuals who do not appear on the report will be reviewed.
7	Beneficiary for survivor income benefit payments does not appear on the SSA death file.	Compare the beneficiary for the survivor income benefit payments to social security administrative death file.	Beneficiaries who appear on the social security administrative death file report will be reviewed.
8	Beneficiary for survivor income benefit payments has not remarried.	For selected claims review Accurint information to note if the beneficiary has remarried.	Beneficiaries who appear to be remarried in Accurint will be reviewed.
9	Improper or incorrect information is entered into the claim payment system	Compare the date of birth, date of death to the date claim that was submitted.	All claims will be reviewed.
10	Claims are paid out for benefits in the additional insurance policy system.	Compare the benefit amounts for group from the additional insurance policy system to the amount paid on the claims on the claim payment system.	All outputs will be reviewed.
11	Amount of paid claim is significantly different from other paid claims from the same group	Compare the payment to other payments in the group to find outliers (payments that are substantially above/below the normal payment).	All outputs will be reviewed.
12	Interest payments are not calculated accurately.	Take the interest rates payment and recalculate it by taking the interest rates by states and multiplying it by the benefit amount.	All outputs will be reviewed.
13	Claim payment data does not balance to the general ledger.	Take random days of claim payments and trace it to the general ledger.	All outputs will be reviewed.
14	Security access individuals have update capabilities to the eligibility system and the claim payment system.	Compare the individuals with update capabilities in the claim payment system to individuals with update capabilities in eligibility system.	Follow-up with system administrator about individuals who have update capabilities in both systems.
15	Inappropriate or unauthorized activity is performed in the claim payment system.	Compare the current system access to an active HR listing.	Follow-up with system administrator about individuals who are terminated and have system access.
16	Benefit amount is not correct	Compare the eligible benefit information to the claim benefit amount.	All outputs will be reviewed.

The nature of group life insurance carries many risks for policy administration and audit. Internal auditors are well aware of the problems and shortcoming of their audit procedures. Therefore, the insurance company is seeking innovative solutions to control and reduce the risk of fraudulent claims.

5.5 Data

5.5.1 General Information

Figure 5.1depicts the group life claim process. The insurance company receives the data in paper format. The insurance company then scans the claim document into the system as a PDF file. The information will be input into the claim payment systems manually, resulting in several potential errors, (e.g. wrong date, typographical error, and misspelling). Some mistakes can be considered as unintentional ones. For example, several date attributes are entered carelessly. There are several instances where the birth date entered would make the claimant a toddler when deceased. In the case of group life claims offered to working people, these values (young age) are clearly invalid.

There are cases where the insured's death dates are prior to birth date and/or employment dates. Other mistakes may not be easily identified. For example, by using the data, a calculated age of the insured can be reasonable (i.e. they could legally be employed); however, another attribute indicated that they are retired from the company and/or died of natural causes. Some may argue that the retired date can be used to estimate the age and/or birth date. However, one insured can retire at age 60; while another retires at age 50. It is thus impossible to determine age, and therefore claim validity, from retirement date.

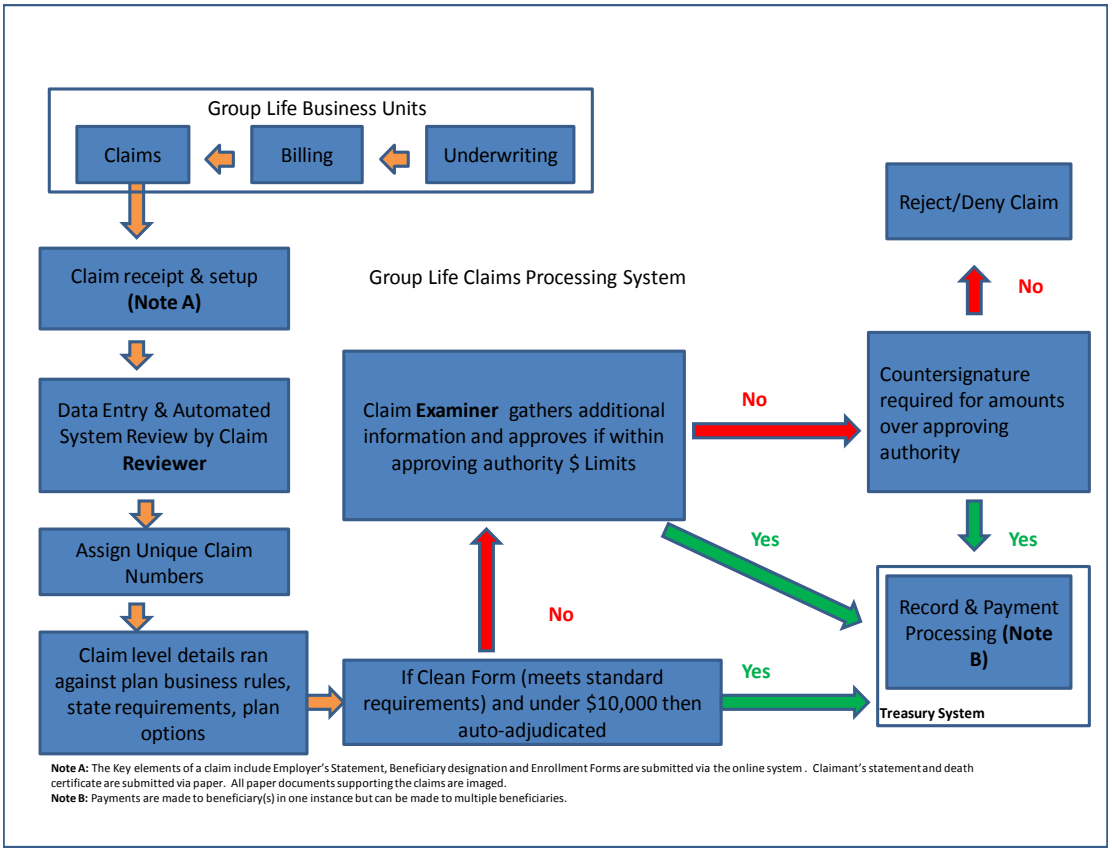


Figure 5.1Group Life Claim Process

The claim received would be identified by claim id (CLM_ID). In the claim payment system, each record represents individual payments. The data set are the records of group life claim payments made from 2008-2009. There are a total of 312,158 records in the file, each representing a payment. There are two types of payments: beneficiary and interest. An individual can have multiple policies, and a single policy can include multiple beneficiaries. Therefore, a single claim can be related to multiple beneficiaries and/or multiple policies. Moreover, if a claim is not paid out at the time of death or the submission, it will accumulate interest. As a result, it is possible that a claim can have multiple records. It is normal that more than one record would be related to a single CLM_ID. Therefore, in the original data set, the CLM_ID would not be a unique

identifier of the record. However, each claim is referred to by CLM_ID. They are approved, denied or frozen by CLM_ID. Therefore, the analysis will be performed on and presented by CLM_ID

From the 312,158 records, there are 181,176 claims in the data set. The distribution of claim by quarter is listed in Table 5.2

Table 5.2 Distribution of Claim by Quarter

Period	Number of Claim
Q1 2008	36208
Q2 2008	36408
Q3 2008	34316
Q4 2008	34164
Q1 2009	40080

5.5.2 Attributes

The data is comprised of 208 attributes related to information of group life claims. The attributes are categorized into 6 groups.

- Insured.
- Dependent
- Coverage
- Group / Company
- Beneficiary
- Payment.

Many attributes are left blank, either because the fields have not been filled in, or because the attributes are not used. From the total 208 attributes, 92 attributes have more than 15% missing values, 21 attributes have a single value, 15 attributes are identification

type(i.e. Name, Last name, Tax ID, Customer ID, Employee ID and etc.), and 8 attributes contain date related data. If the date related attributes are not related directly to the payment, they are known to be inaccurate. In other words, if the date is not a payment date (either interest or beneficiary payment), its accuracy cannot be guaranteed. Though there might be some input controls to ensure that improper and/or incorrect information was not entered into the database, the input controls may not be able to detect when employees are deliberately entering inaccurate data. Therefore, these attributes should be excluded from the analysis. A summary of this basic information is presented in Figure 5.2. The remaining attributes are those attributes which do not have these shortcomings. The absence of these deficiencies cannot guarantee that they will be useful for all analysis. The list of these attributes is shown in Table 5.3 .

After checking the values of the remaining attributes, other data quality problems become apparent. Several attributes are designed to store coverage information. There are two main types of coverage amount: flat and multiple factor. Flat coverage refers to a fixed dollar amount. Multiple factor coverage can be based on many different factors such as 2X monthly salary, 1X annual income, etc. The data will be easily interpreted if the company uses a certain or fixed number of attributes to collect this information. There are several attributes supposedly holding the coverage information; for example, coverage flat amount, coverage multiple factor, coverage percentage, coverage benefit percentage, and coverage benefit flat amount. The company's recording policies are not consistent. The same data element may be recorded in one of many attributes. In addition, there are cases where the coverage is fixed; however, the information on multiple factors

is also present. Therefore, it is impossible to derive the exact amount of payment by combining or calculating values from attributes holding related information.

After multiple examinations of the raw data file and consultation with the domain experts (internal auditors), suggestions on attribute selection were developed. Based on current control tests (see Table 5.1), the major concern of this group life business unit is the payment. Several existing tests relate to the reasonableness of the interest payment and the beneficiary payment. In addition, the internal auditors specifically communicate that they are in search of better and more useful techniques to test the reasonableness of the values.

All Attributes	208
Less:	
Attributes with more than 15% missing values	-92
Attributes with single values	-22
Identification type of attributes (TAXID, CUSTOMER ID, EMPLOYEE ID and etc)	-15
Date information (such as birthdate, hiring date, final work date and etc.)	-8
Remaining attributes	71

Figure 5.2 Summary of Attribute Information

Table 5.3 List of Remaining Attributes

Attribute Name	Expanded Attribute Name	Attribute Name	Expanded Attribute Name
CLM_ID	Claim ID	Insured_CLI_CITY_NM_TXT	CITY
CLM_STAT_CD	Claim Status Code	Beneficiary_CLI_PSTL_CD	ZIPCODE
BASE_ANN_INCM_AMT	Base Annual Income Amount	Insured_CLI_ADDR_LN_1_TXT	ADDRESS
TEAM_CD	Team assigned to claim in Oriskany	Company_Division_CLI_CTRY_CD	COUNTRY
COMB_RSK_POOL_AMT	Combined Risk Pool Amount	MULT_LVL_INCR_IND	Multiple Level Increase Ind
BNFY_TYP_CD	Beneficiary - Type	XCES_RSK_POOL_IND	Excess Risk Pool Indicator
Beneficiary_CLI_CTRY_CD	US	COMB_RSK_POOL_IND	Combined Risk Pool Indicator
FRGN_RES_IND	Foreign Resident Indicator	SITUS_ST_CD	Situs State code
PAYE_TYP_CD	Payee Type code	Insured_CLI_CRNT_LOC_CD	STATE
PMT1_AMT	Payment Amount 1	PMT1_MTHD_CD	Payment method payment 1
PMT_DT	Payment Date	Beneficiary_CLI_CRNT_LOC_CD	STATE
PMT_STAT_CD	Payment Status Code	DLAY_PMT_INT_CD	delay payment interest code
SIB_INS_IND	SIBI Insurance Indicator	Insured_CLI_SEX_CD	Sex
Beneficiary_CLI_CITY_NM_TXT	CITY	Insured_CLI_PSTL_CD	ZIPCODE
BNFY_REL_INSRD_CD	Beneficiary Relation to the insured	CUST_CITY_TXT	CITY
PMT_MTHD_CD__T5BEN_	Payment Method	CUST_STATE_CD	STATE
ABS_ASIGN_IND	Absolute Assignment Indicator	PMT_MTHD_CD__T5CVG_	Payment Method code
INS_CNCL_IND	Insurance ever Cancelled Indicator	INSRD_JOB_STAT_CD	Job Status Code
CLMT_STMT_SIGN_IND	Claimant Statement Sign indicator	CUST_ADDR_LN_1_TXT	ADDRESS
BCKUP_WTHLD_IND	Backup Withhold Indicator	CUST_PSTL_CD	ZIPCODE
MAIL_TO_EMPLR_IND	Mail to Employer Indicator	MULT_PMT_MTHD_IND	Multiple Payment method indicator
W8_BNFY_IND	W8 Beneficiary Indicator	SEND_CHK_TO_CD	Send Check to code
ADDL_PMT_IND	Additional Payment Indicator	Beneficiary_CLI_SEX_CD	Sex
CVG_NUM	Coverage Number	Insured_CLI_INDV_TITL_TXT	Title
CVG_DESC_TXT	Coverage Discription	PERF_DY_DUR	Performance Guarantee indicator
CLM_CVG_AMT	Claim Coverage Amount	NOTI_CLM_PMT_IND	Notification of Claim Payment Ind
CVG_STAT_CD	Coverage Status code	PARTY_3RD_ADM_IND	TPA Indicator
BASE_CVG_NUM	Base Coverage Number	FORM_712_IND	712 Form Indicator
CVG_FLAT_AMT	Coverage Flat Amount	Insured_CLI_MARIT_STAT_CD	Marital Status
CVG_MULT_FCT	Coverage Muliple Factor	Beneficiary_CLI_INDV_TITL_TXT	Title
CVG_PCT	Coverage percent	MINR_BNFY_IND	Minor Beneficiary Indicator
CVG_BNFT_PCT	Coverage benefit percent	SPCL_HNDL_IND	Special Handling required
CVG_BNFT_FLT_AMT	coverage benefit flat amount	Insured_LOSS_TYP_CD	Loss Type Code
BNFY_DESGNT_CD	Beneficiary Designation code	Insured_MANNER_LOSS_CD	Manner of Loss Code
HLD_HRMLESS_IND	Hold Harmless Indicator	Insured_CAUSE_LOSS_CD	Cause of Loss code
PAR_IND	Par/Non-Par indicator		

Because of data quality issues and after consulting with internal auditors, a new dataset was created based on the original data. Four newly created attributes were selected for clustering:

- Percentage: Total interest payment / Total beneficiary payment
- AverageCLM_PMT: Average number of days between claims received date and the payment date (a weighted average is used because a claim could have multiple payment dates)
- DTH_CLM: Number of days between death date and claim received date.
- AverageDTH_PMT: Average number of days between death date and payment date (a weighted average is used because a claim could have multiple payment dates).

These attributes were normalized so they could be compared, minimizing the effect of scale differences. These attributes will be used for cluster analysis.

5.6 Methodology

5.6.1 Clustering Procedure

Internal auditors perform quarterly audits. In order to mesh with the internal audit analysis, the clustering procedure will be performed using the data by quarter. For this initial work, the latest data, Q1 of 2009 will be used for the analysis.

Because all attributes are numeric, simple K-mean clustering is selected as the clustering procedure. K-mean is a simple, well-known algorithm for clustering. It is less computer intensive than many other algorithms, making it a preferable choice for large datasets (Tan et al, 2006).

Because K-mean does not have the option to automatically use the number of clusters to group the data, the number of clusters must be pre-selected. No matter how many number of clusters the data set must be grouped to, the following steps would generally the same.

The second step for K-mean clustering is to place each observation into a cluster. This step can be done randomly or systematically. Centroids (or Center of cluster) must be selected, then each observation is assigned to the closest centroid.

The third step would be to compute the distance between each observation and the centroid. If the observation is not currently a member of the cluster with the closest centroid, the observation must be reassigned to the new cluster, then new centroids will be recalculated. The process from step three will repeat until there is no new assignment. The steps in K mean clustering could be explained as follows (Roiger et al, 2003):

> *Here is the algorithm*
> 1. *Choose a value for K, the total number of clusters to be determined.*
> 2. *Choose K instances (data points) within the dataset at random. These are the initial cluster centers.*
> 3. *Use simple Euclidean distance to assign to remaining instances to their closest cluster center.*
> 4. *Use the instances in each cluster to calculate a new mean for each cluster.*
> 5. *If the new mean values are identical to the mean values of the previous iteration the process terminates. Otherwise, use the new means as cluster center and repeat steps 3-5.*

One way to measure the quality of a clustering is to use sum of squared error (SSE) by computing the error of each data instance to its closest centroid, then computing the total sum of the squared error (Tan et al, 2006). Clusters produce the lowest SSE when the number of clusters is equal to the number of instances. An obvious and probably simplest way to reduce SSE is to increase the number of clusters. Adding the

first cluster will decrease the SSE substantially. The higher number of clusters, the lower SSE. However, at some point the marginal gain (the decreasing SSE) will be dropped. An ideal number of clusters should be the one where adding an additional cluster will not substantially reduce the SSE. A graph should be plotted to show the relationship between the number of clusters and the resulting SSE in order to find "elbow" (Alpaydin, 2004). The drop in the marginal gain will create the elbow in the graph. Several numbers of clusters have been tried. The resulting sums of squared errors are used to plot the graph to find the suitable number of clusters. The number of clusters which create the elbow in the graph is selected. Observations are grouped to a cluster. For the first combination, representing the interest and total length of time in the claim payment process (i.e. interest and death to payment), Percentage and AverageDTH_PMT are used. For the second combination, representing the interest and the length of time in the claim payment process in greater detail (i.e. interest, death to claim, death to payment, claim to payment), all four variables are used.

The software packages used are WEKA[1] and SAS. The data set will be cleaned and transformed using SAS. The clean data is then exported into CSV format and then converted into ARFF format in order to feed into WEKA.

5.6.2 Anomaly Detection

This research examines both individual observations and small clusters as possible outliers. Most data points in the dataset should not be outliers. The outliers are then identified in three ways:

[1] WEKA (**W**aikato **E**nvironment for **K**nowledge **A**nalysis), developed by The University of Waikato, New Zealand, is an open source for machine learning written in Java. It is available at http://www.cs.waikato.ac.nz/ml/weka/. It contains a large collection of tools for standard data mining tasks such as data preprocessing, feature selection, classification and clustering. More details on WEKA can be found at the website and Hall et al (2009).

- First, observations that have low probability of being a member of a cluster (i.e. are far away from other members of the clusters) are identified as outliers. The probability of 0.6 is used as a cut-off point.
- Second, clusters with small populations should be considered outliers. In this aspect, clusters populated with less than 1% of the whole population are considered as outliers.
- Third, rule based extraction will be developed to aid anomaly detection.

Most clusters have large populations. Some well-populated clusters may still have suspicious characteristic. Therefore, in addition to cluster-based outliers, rule-based extraction might be applied in order to select a number of observations from highly populated clusters and flag them as suspicious. These rules can be developed by consulting with business managers with domain knowledge and internal auditors with experience auditing the unit.

Based on the previous experiences, rules can be created. Internal auditors learn from previously detected frauds how they were committed, then attempt to create detection and protection for such incidents. Business rules and policy are set up as guidance. If the rules are not observed by employees, company can suffer losses. Therefore, testing if the business rules and policies are followed is important. Previous fraud cases and business rules are used in creating a rule based detection system.

5.6.3 Rule-Based Anomaly Detection

Some rules were derived from examination of the data. Internal auditor found that some data fields have been entered carelessly. Some information can be verified with government issued data. However, some wrong dates can be identified easily without any

external help. For instance, the insured's calculated age should not be lower than sixteen, the legal minimum employment age. After a simple calculation of the insured age, errors in data entry have been uncovered in many claims.

In order to further identify suspicious claims, the following indicators/rules were created.

- **Age related rules:**
  - Age1= "Y" if Birthday and/or Death date is available, otherwise Age1= "N"
  - Age2= "Y" if the calculated age is proper.

    For example, If the insured's age, calculated from birth date – death date, is lower than 16, Age2= "N"

    If the insured age is lower than 50 and the INSRD_JOB_STAT_CD is "R"(for retired employee), then Age2= "N"
- **Causes/Manner of loss relation**
  - CAUSE1= "Y" if both Insured_MANNER_LOSS_CD AND Insured_CAUSE_LOSS_CD are available
  - CAUSE2= "Y" if the relationship between manner and cause of loss are reasonable.

    Insured_MANNER_LOSS_CD is related to the manner that a person died. It is divided into 4 groups.

    AC: Accident

    HO: Homicide

    NC: Natural Causes

PI: Pending Investigation

SU: Suicide

UD: Undetermined

Insured_CAUSE_LOSS_CD is related to the specific reason that a person died such as specific disease, type of accident and etc. In order to check the relationship of manner and cause of death the possible cause are divided into 4 groups

Diseases causes

Accidental causes

Undetermined causes

Suicidal causes

If the manner is “AC”, the cause should not be diseases OR suicidal.

If the manner is “HO”, the cause should not be diseases OR suicidal.

If the manner is “NC”, the cause should not be accidental OR suicidal.

– CAUSE3= “Y” if the manner is NOT “PI-pending investigation” OR “UN-undetermined” OR the cause of loss is “UNDT-undetermined”

The claim relating to unresolved death or pending investigation should not be paid.

- **Date Related**
  - DATE1= “Y” if the payment date is AFTER the claim received date.

Payment date should come after the claim received date. However, some payment date appeared to precede their respective the received dates.

  - DATE2= “Y” if the claim is received AFTER the death date.

Life claim should be received, in most case, after a person died. However, in some case, the claim is received before the death if the insured is terminally ill.

- DATE3= "Y" if, in the case of SUICIDE, the payment date is at least 2 years AFTER the death date.

Company policy dictates that payout will not occur until two years after death in the case of suicide.

- **Beneficiary Tax ID**
  - BID= "Y" if the beneficiary has a tax id.

When the beneficiary does not have a tax id, a default number '99999999' is assigned to the beneficiary. If the default number has been used, it would be extremely difficult to verify the duplication or the existence of the specific beneficiary. It is possible to create a fictitious person to receive a claim.

Having failed any specific test does not guarantee that a claim is fraudulent. There can be legitimate reasons for such discrepancies. For example, if a beneficiary is a foreigner, he/she will not have a tax id. If a claim is an accelerated benefit, the claim will be received legitimately before death.

Failing these rules, however, can be an indicator of possible deceit. Each test failure will be given a suspicious score of "1". If it passes ("Y"), the score would be "0". If it fails, the score will be "1". The higher the score, the more suspect is the claim.

Different clusters can have different score distributions. The highest score for one cluster can be different from another. Selecting cut-off points for the cluster will require input from the domain experts, such as business managers and internal auditors.

5.7 Results

The 40,080 claims paid in the first quarter of 2009 are used in the analysis. Two different combinations of attributes are used for clustering. First, the Percentage and AverageDTH_PMT are used for initial clustering. Several numbers of clusters have been tested. The relationship between the number of clusters and resulting sum of squared errors is plotted as shown in Figure 5.3. From the graph, it is clear that adding an additional cluster will reduce the SSE. However, at some point, the SSE will be reduced at significantly lower rate. When the number of clusters is eight, adding an additional cluster will insignificantly reduce the SSE from 3.9 (in eight clusters) to 3.4 (in nine clusters). Therefore, in this particular dataset, the number of clusters selected should be eight.

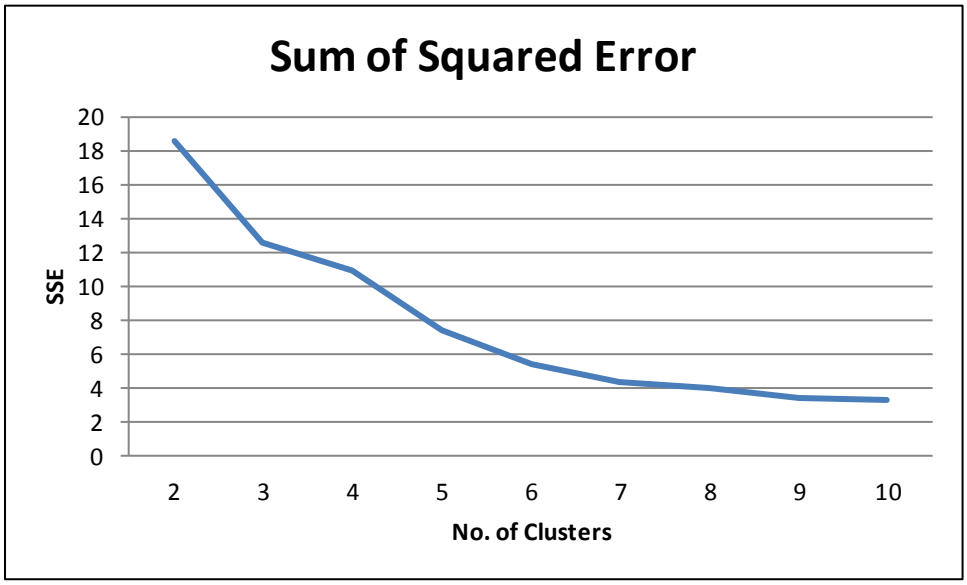
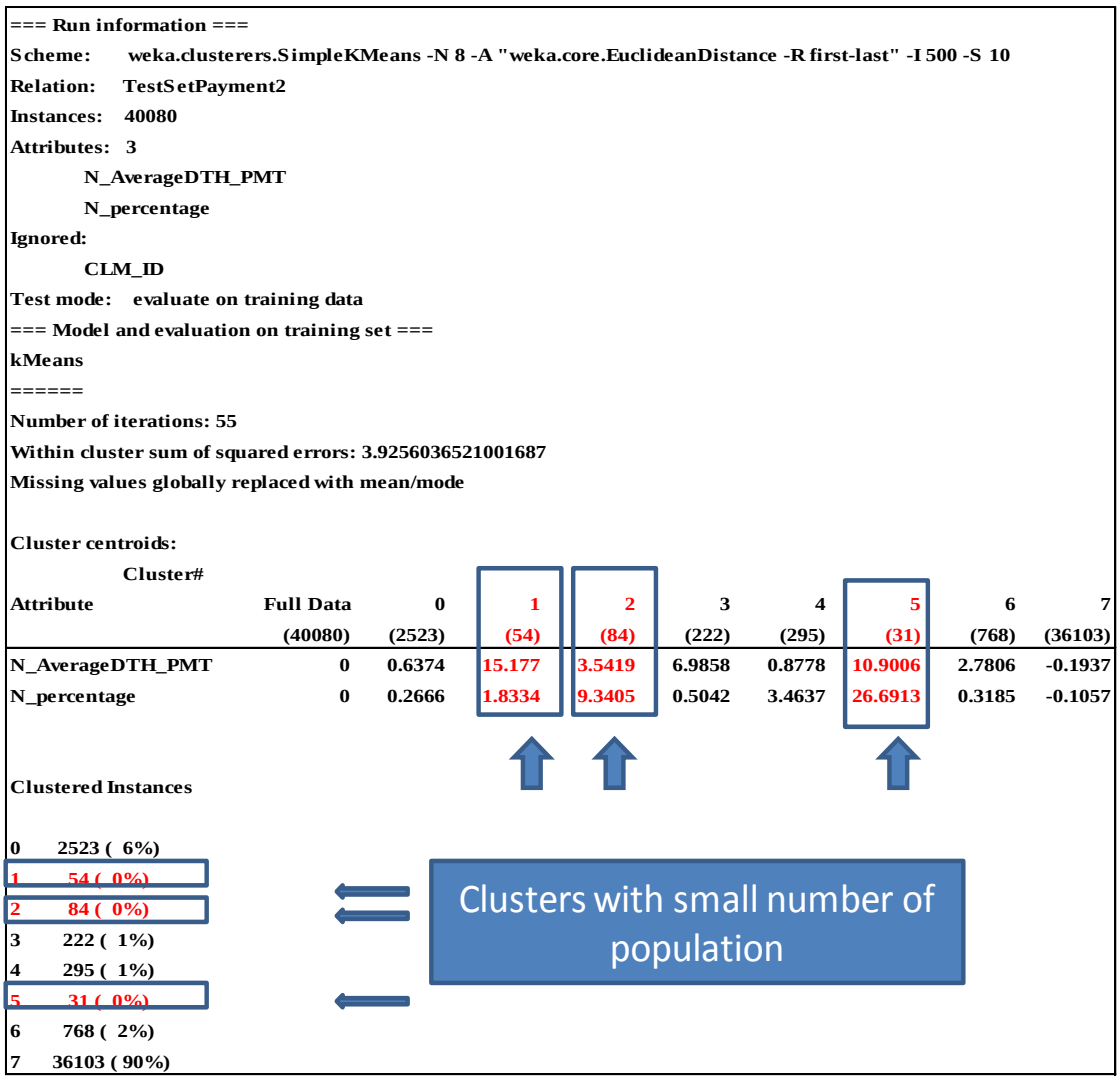


Figure 5.3Number of Clusters and Resulting Sum of Squared Error: 2 Attributes

The results from WEKA are represented in Table 5.4.

Table 5.4 Result of Cluster Analysis using Two Attributes from WEKA (Enhanced)



```
=== Run information ===
Scheme:       weka.clusterers.SimpleKMeans -N 8 -A "weka.core.EuclideanDistance -R first-last" -I 500 -S 10
Relation:     TestSetPayment2
Instances:    40080
Attributes:   3
              N_AverageDTH_PMT
              N_percentage
Ignored:
              CLM_ID
Test mode:    evaluate on training data
=== Model and evaluation on training set ===
kMeans
======
Number of iterations: 55
Within cluster sum of squared errors: 3.9256036521001687
Missing values globally replaced with mean/mode

Cluster centroids:
                        Cluster#
Attribute               Full Data          0          1          2          3          4          5          6          7
                        (40080)       (2523)       (54)       (84)      (222)      (295)       (31)      (768)    (36103)
N_AverageDTH_PMT               0       0.6374     15.177     3.5419     6.9858     0.8778    10.9006     2.7806    -0.1937
N_percentage                   0       0.2666     1.8334     9.3405     0.5042     3.4637    26.6913     0.3185    -0.1057

Clustered Instances

0      2523 (  6%)
1        54 (  0%)
2        84 (  0%)
3       222 (  1%)
4       295 (  1%)
5        31 (  0%)
6       768 (  2%)
7     36103 ( 90%)
```


For the first set of clusters using two attributes, eight clusters are formed. About 90% of claims are clustered into cluster7 and 6% are in cluster0 (as shown in Table 5.4). Three clusters (cluster1, cluster2, and cluster5) have membership of less than 1% of the total. The numbers of claims in those clusters are 54, 84 and 31 respectively. Examining the characteristics of these less populated clusters, some suspicious characteristics should

be mentioned. Claims in these clusters have high interest/beneficiary payment percentage and/or claims with a long period of time from death dates to payment dates. Claims in cluster5 have high interest / beneficiary payment percentage and a long period between the death dates and the payment date. Cluster1 claims have long period from death to payment dates. Claims in cluster2 have high interest/beneficiary payment. The total number of claims identified as possible anomalies from cluster-based outliers is 169. In addition to identifying small clusters, the probability of individual observations' cluster membership is examined. The claims, which have lower than 0.6 probabilities of belonging to the cluster they are assigned to, are identified as possible anomalies. 568 claims fit this criterion. The visualized results are shown in Figure 5.4.

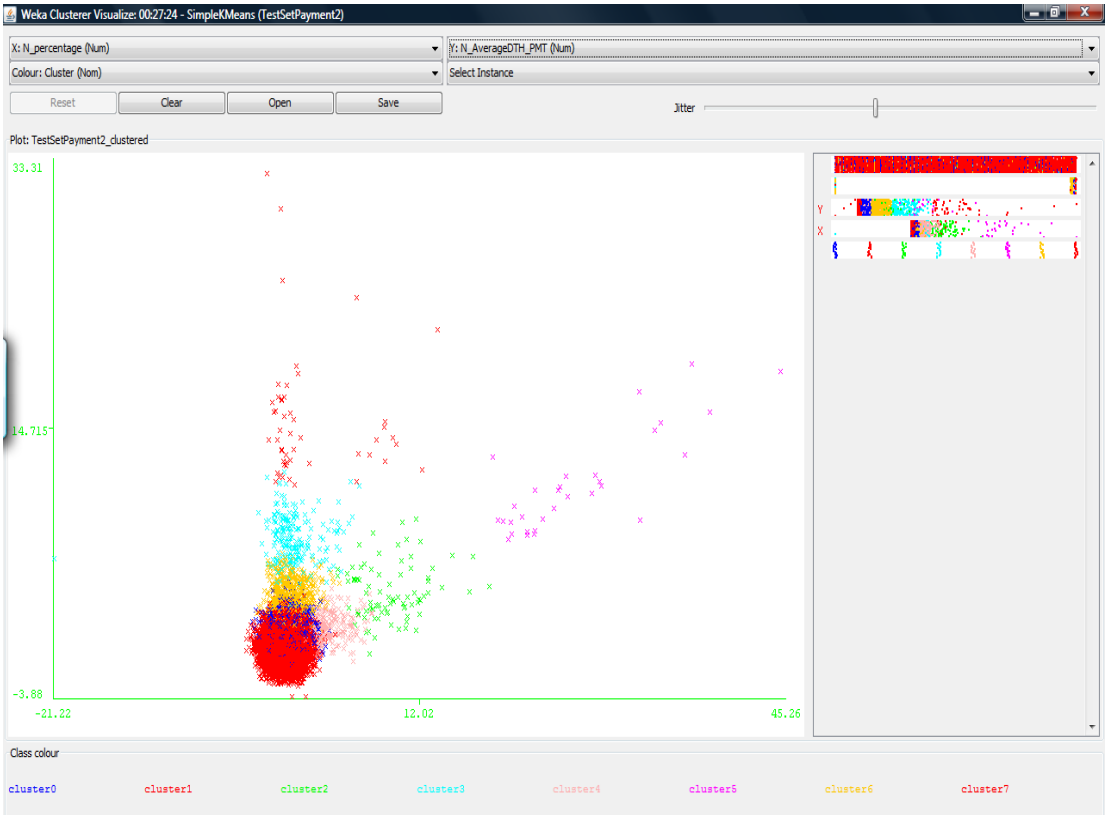


Figure 5.4 Visualization of the Cluster Assignment for 2 attributes clustering; N_Percentage and N_AverageDTH_PMT.

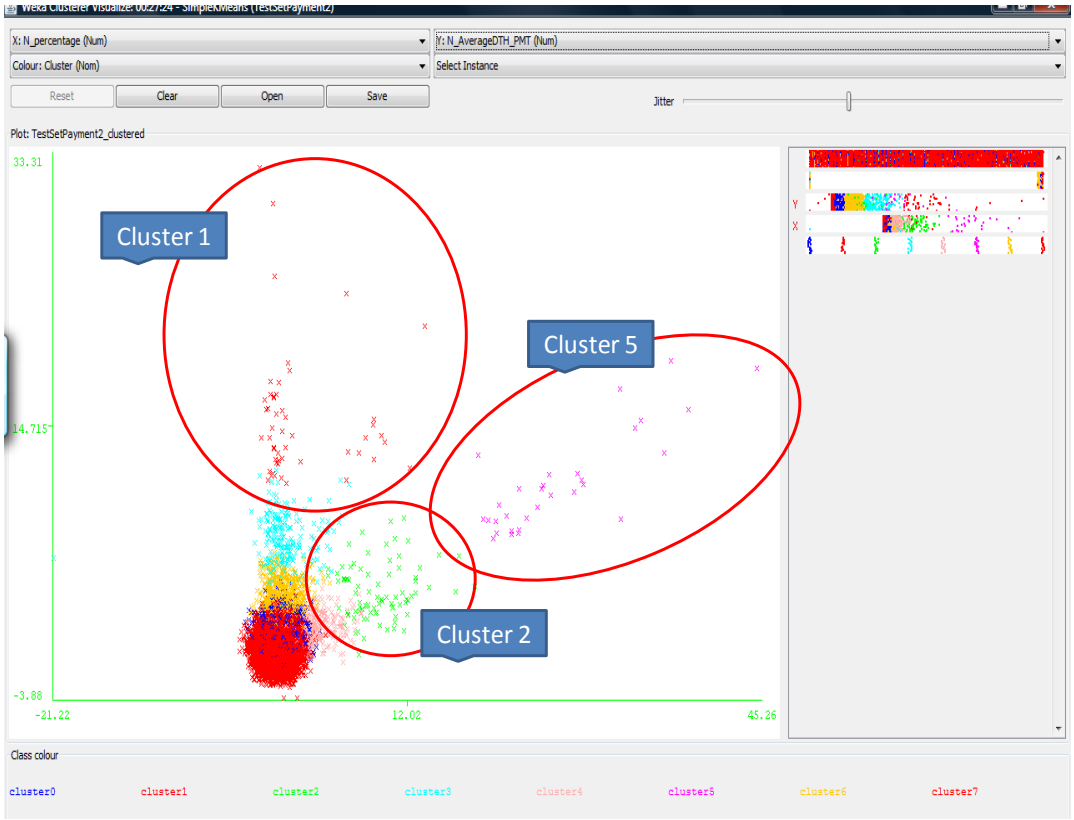


Figure 5.5 Visualization of the Clustering Result (Two Attributes) with Cluster Marked

It is clear that cluster1, cluster2 and cluster5 have fewer members and are sparser. Characteristics of claims in these clusters are different from the majority of claims in other clusters. Having different characteristics does not necessarily signal abnormality or fraud. There are possibly legitimate reasons; for example, a claim may have high interest because it was in the system for a long time. If the insured died a long time before the claims are submitted; accumulated interests will be high. These legitimate reasons, however, should be considered with caution. Several questions should be asked. For example,

- If the claim was in the system for a long time
  - Why were the claims in the system for that long?
    - Document issues

- Was it because the document was incomplete?
- What document was it?
- Why did it take long time?

▪ Beneficiary issues

- Was it because difficulty in tracking down the beneficiaries?
- Why was it difficult?
- Were they out of the country?
- Did they have their name changed?
- What were the dollar amounts they received?

– If the insured died a long time before the claim was submitted

o Why did it take time? Was it because the beneficiaries were unaware of the policy?

o Who were the beneficiaries? What were the dollar amounts they received?

Answers to these questions should not be taken lightly. Knowledge of such a policy, if fell into wrong hands, might create an opportunity for someone to commit insurance fraud. For example, if it has taken a long time to collect the document because the beneficiaries are out of reach, how can we be sure that the individuals who appear to be the previously unreachable beneficiaries are the person who they say they are? What if someone else is hired to pretend to be the missing beneficiaries? What if the real beneficiaries are unaware of the policy, but someone else pretends to be them and cash out the payment? When an insurance claim is submitted but not paid for a long time, or it

has taken a long time to submit, and then one day it gets paid, the internal auditor should exert caution. There are several possibilities and opportunities for fraud.

Internal auditor should check not only those claims with no explanation, but also those with unsound explanation.

For the second set of cluster analysis, four attributes are used. Several numbers of clusters have been tested to find the suitable one. For this data set with four attributes, number of cluster selected is thirteen. The Figure 5.6 illustrates that when an additional number of clusters is added, the resulting sum of squared error is decreased, until a certain point similar to the previous case with two attributes..

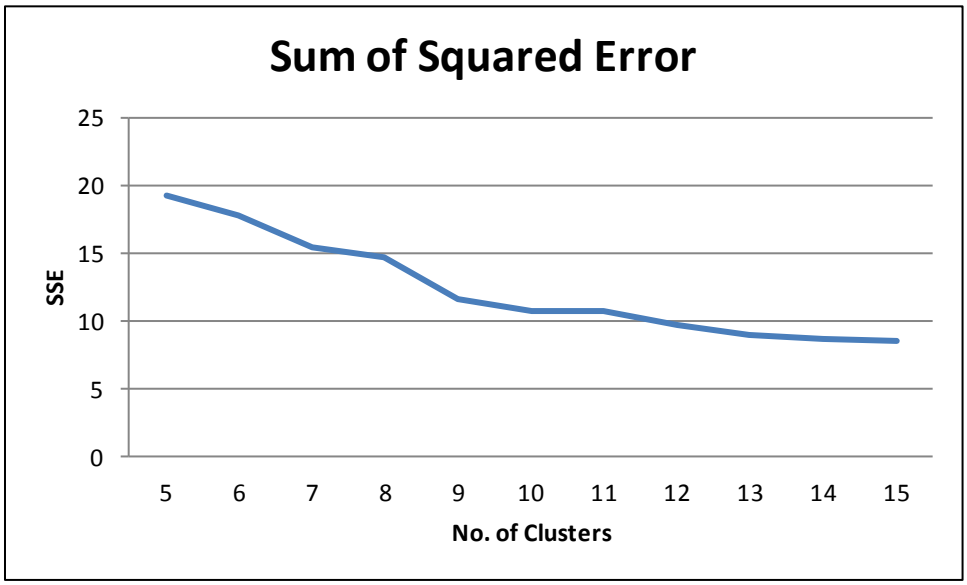
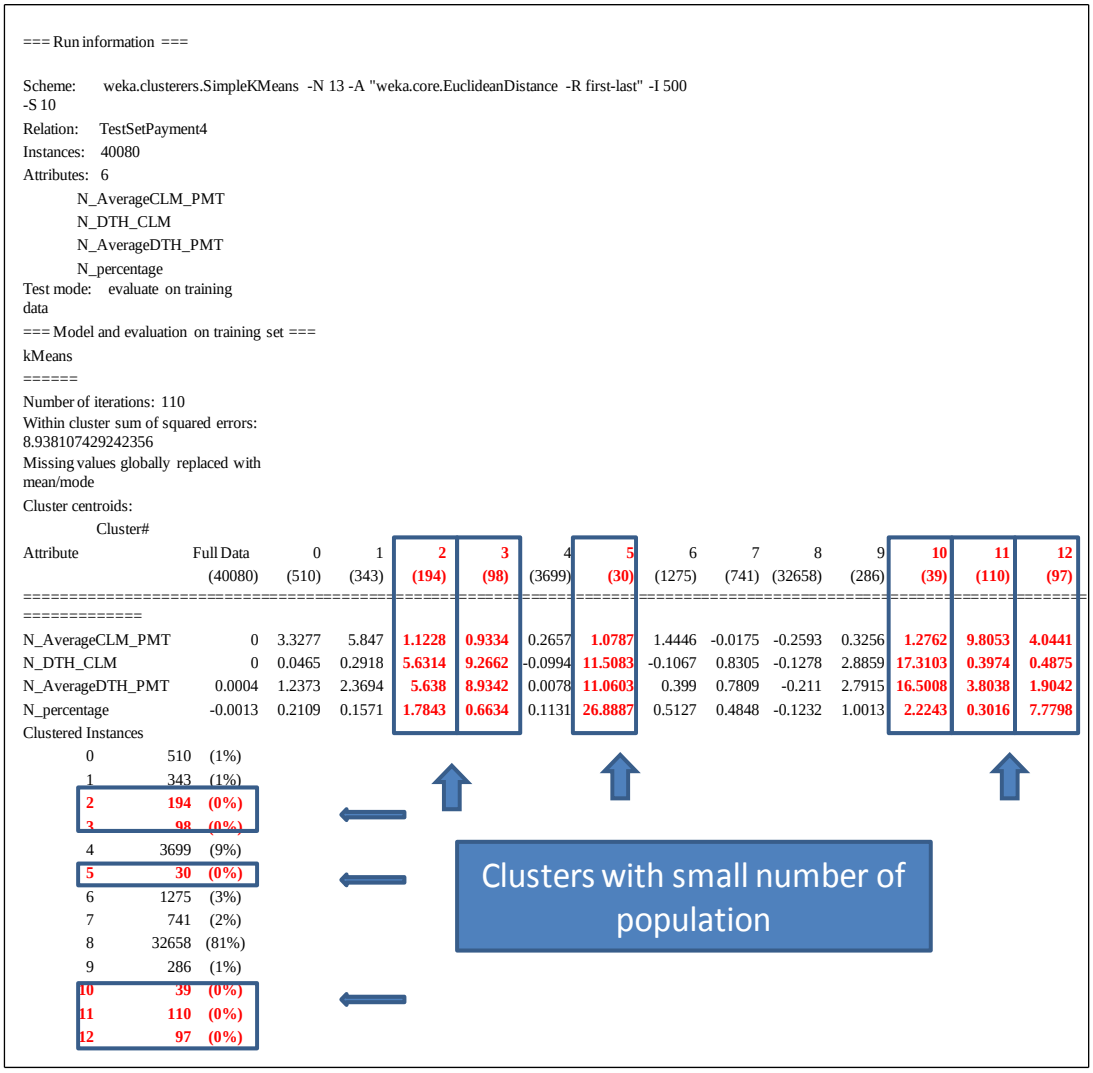


Figure 5.6Number of Clusters and Resulting Sum of Squared Errors: 4 Attributes

Table 5.5 Result of Cluster Analysis using Four Attribute from WEKA (Enhanced)



```
=== Run information ===

Scheme:       weka.clusterers.SimpleKMeans -N 13 -A "weka.core.EuclideanDistance -R first-last" -I 500
-S 10
Relation:     TestSetPayment4
Instances:    40080
Attributes:   6
              N_AverageCLM_PMT
              N_DTH_CLM
              N_AverageDTH_PMT
              N_percentage
Test mode:    evaluate on training
data

=== Model and evaluation on training set ===

kMeans
======

Number of iterations: 110
Within cluster sum of squared errors:
8.938107429242356
Missing values globally replaced with
mean/mode
Cluster centroids:
                        Cluster#
Attribute               Full Data       0       1       2       3       4       5       6       7       8       9      10      11      12
                          (40080)   (510)   (343)   (194)    (98)  (3699)    (30)  (1275)   (741) (32658)   (286)    (39)   (110)    (97)
=============================================================================================================================================
N_AverageCLM_PMT                0  3.3277   5.847  1.1228  0.9334  0.2657  1.0787  1.4446 -0.0175 -0.2593  0.3256  1.2762  9.8053  4.0441
N_DTH_CLM                       0  0.0465  0.2918  5.6314  9.2662 -0.0994 11.5083 -0.1067  0.8305 -0.1278  2.8859 17.3103  0.3974  0.4875
N_AverageDTH_PMT           0.0004  1.2373  2.3694   5.638  8.9342  0.0078 11.0603   0.399  0.7809  -0.211  2.7915 16.5008  3.8038  1.9042
N_percentage              -0.0013  0.2109  0.1571  1.7843  0.6634  0.1131 26.8887  0.5127  0.4848 -0.1232  1.0013  2.2243  0.3016  7.7798
Clustered Instances
0       510 (1%)
1       343 (1%)
2       194 (0%)
3        98 (0%)
4      3699 (9%)
5        30 (0%)
6      1275 (3%)
7       741 (2%)
8     32658 (81%)
9       286 (1%)
10       39 (0%)
11      110 (0%)
12       97 (0%)
```


About 81% of claims fall into cluster8. Six clusters are populated with less than 1% of the claims (from Table 5.5). These are cluster2, cluster3, cluster5, cluster10, cluster11 and cluster12. The numbers of claims in those clusters are 194, 98, 30, 39, 110 and 97, respectively. Because of time and budget constraints, it is impractical to follow up on all of the claims in the suspicious clusters. Therefore, not all small clusters are selected for further investigation. Not all available explanation will sound reasonable. All the small clusters should be closely examined. From these six small clusters, the one that has interesting characteristics and should be selected for the follow up in greater details is

cluster12. This cluster has a high interest/beneficiary percentage, while the length of time from the death to payment date is not as high. The length of time is a very important factor for determining the amount of interest. The important question the internal auditor should ask is why the interest rate is high. The explanation given should also be reviewed to check for its validity.

In addition to identifying small clusters as possible anomalies, the probability of individual observations' cluster membership is examined. A distance-based outlier in a dataset is a data instance having a distance far away from the center of the cluster. Probability distribution over the clusters for each data instance is calculated. The data instance which has the highest probability lower than the cut-off point will be identified as possible outliers. Using probability of 0.6 as the cutoff point, 325 claims and 547 claims are identified as possible anomalies from two attributes and four attributes clustering results respectively.

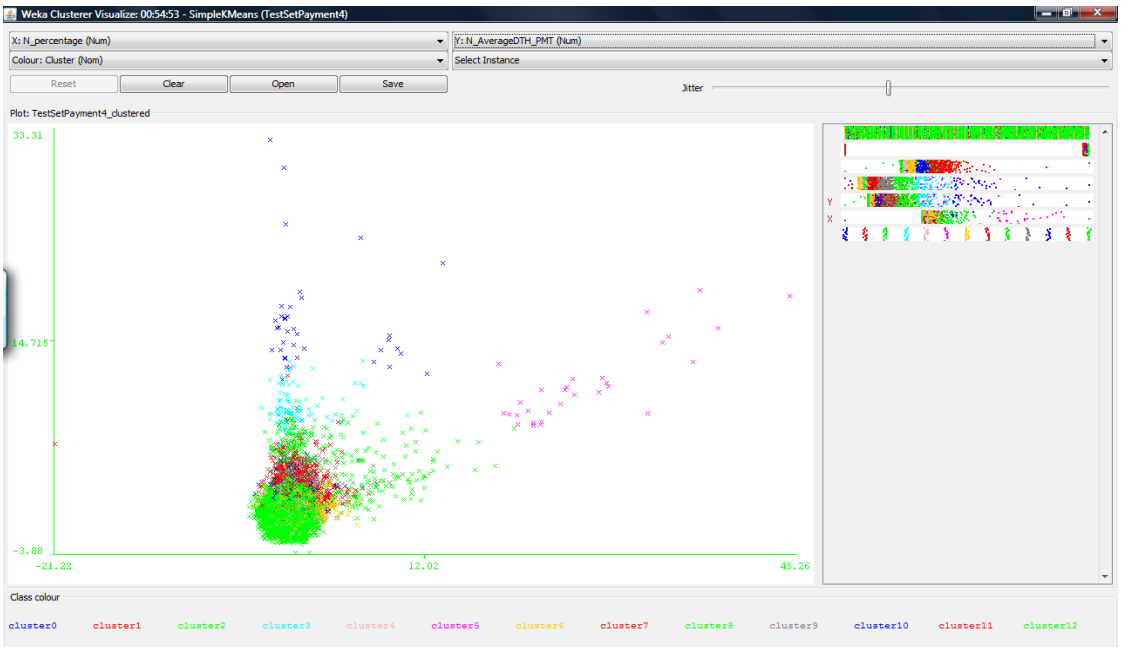


Figure 5.7 Visualization of the Cluster Assignment for 4 attributes clustering: N_Percentage, N_AverageDTH_PMT, N_AverageCLM_PMT, N_DTH_CLM.

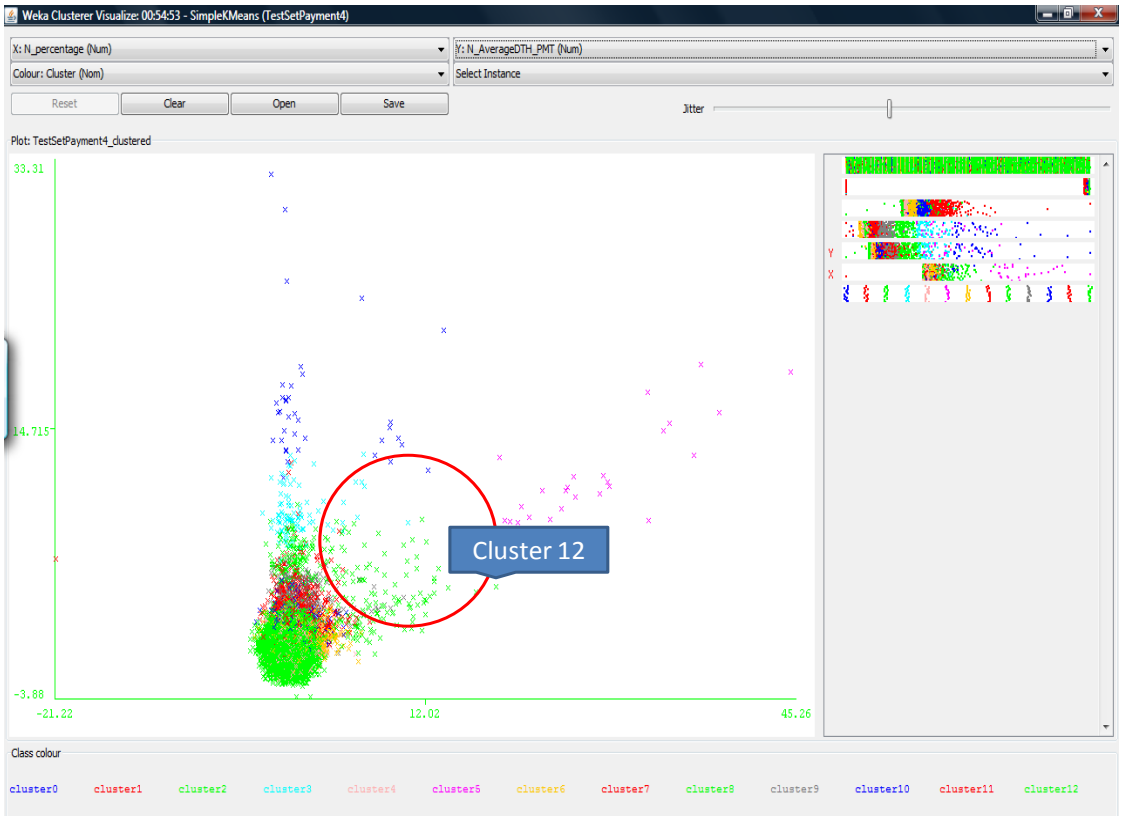


Figure 5.8 Visualization of the Clustering Result (Four Attributes) with Marks

The results from these two settings (two and four attributes) for cluster analysis and its two anomaly detection are presented inTable 5.6.

Table 5.6 Summary of the Results from Cluster Analysis

Cluster Analysis	Cluster-Based Outliers	Distance-Based Outliers
Cluster Analysis with 2 Attributes	169	325
Cluster Analysis with 4 Attributes	568	547

Suspicious claims should be investigated further by the internal auditor to determine the efficacy of the clustering effort. The results from the follow up would help to improve the model.

Time and budget constraints prohibit investigation of all claims in all suspicious clusters. Moreover, some suspicious clusters may be highly populated. Therefore, in addition to cluster-based outliers, rule-based extractions would be used to filter claims for further investigation.

The results from the cluster analysis would be used for this step. All claims would be tested by using the rules in the previous section. The total possible score is nine. The claims which did not pass this filter are summarized in Table 5.7. The results demonstrate that this dataset has quality issues. Several important pieces of information are missing or incorrect (for example, birth date and death date). Some information is not updated (for example, the manner of lose is still shown as pending, while, the payment is made- A claim payment should not be made if the case is still under investigation).

Inquiries regarding these issues did not result in satisfactory conclusion. For example, the company acknowledges the data quality issues; however, instead of expressing an interest in minimizing or eliminating the problems, they accept the bad

quality data and try to work with it. When questions about cases under investigation are asked, the company responds that it is highly likely that the cases have already been concluded but the data have not been updated.

In some cases, failing the rules indicates that domain knowledge is required and further investigation is needed. Cases where claim dates precede death date, for instance, might arouse suspicion. However, if an insured is terminally ill, he/she may need accelerated benefit payments to cover hospital expenses. Therefore, the claim should be submitted, reviewed and paid before the insured dies. For this kind of situation, the insurance company relies on the opinion of the doctor who is taking care of the insured. If the doctor provides proof that the insured is terminally ill, the insurance company will accept the doctor's opinion and approve the payment. If a claim fails this rule test, the internal auditor should first check to see if the insured is terminally ill. If the insured is indeed seriously ill, the claim should not be flagged.

Table 5.7 Number of Claims fails the test (rule-based filtering)

Rules	Number of Claims
If Birthday and/or Death date is **NOT** available	13
If a proper age **CAN NOT** be calculated from the information	18
If both Insured_MANNER_LOSS_CD AND Insured_CAUSE_LOSS_CD are NOT available	269
If the relationship between manner and cause of loss are **NOT** reasonable.	31
If the manner is "PI-pending investigation" OR "UN-undetermined" OR the cause of loss is "UNDT-undetermined	197
If the beneficiary has **NO** tax id	402
If the payment date is **BEFORE** the claim received date	12
If the claim is received **BEFORE** the death date	72
If, in the case of SUICIDE, the payment date is at **LESS THAN** 2 years AFTER the death date	107

The score distribution is presented in Table 5.8 and Table 5.9. The highest scores for each cluster are widely distributed. It appears that no single claim fails multiple rules. Therefore, there is no claim shown with a score higher than 4, and only 16 claims have a total score of 3. Because the highest scores in each cluster are not the same, the investigation thresholds for each cluster should not be the same. For example, only five clusters have the highest score of 3. If the score of three is used as universal cutoff point, there will be only claims from those five clusters. Judgment can also be made if a

universal cut off point is desired. For example, if the score of two is used as a universal cutoff point, there will be a total of 157 claims flagged: 141 claims with the score of 2 and 16 claims with the score of 3. The number of flagged claims from cluster0 and cluster6 can be considered too many for the internal auditor to do the detailed follow-up. If it is more reasonable that some claims from each cluster should be flagged, different cutoff points should then be applied for each cluster.

Table 5.8 Suspicious Score Distribution by Cluster: Two Attributes

	SCORE				
CLUSTER	0	1	2	3	Grand Total
cluster0	2181	289	46	7	2523
cluster1	45	5	4		54
cluster2	83	1			84
cluster3	183	33	5	1	222
cluster4	278	16	1		295
cluster5	31				31
cluster6	534	169	61	4	768
cluster7	35095	980	24	4	36103
Grand Total	38430	1493	141	16	40080

Table 5.8 and Table 5.9 show that suspicious score has no relation with clusters (i.e. 16 claims have the score of 3 from both clustering results). At this stage the rules are created using general business rules and policy. Therefore, the clustering results have no effect on the score. With no rule created from cluster analysis, the potential usages for cluster analysis with these results are that the results can be used for setting the cutoff points.

Table 5.9 Suspicious Score Distribution by Cluster: Four Attributes

	SCORE				
CLUSTER	0	1	2	3	Grand Total
cluster0	336	136	35	3	510
cluster1	192	110	40	1	343
cluster2	169	19	6		194
cluster3	81	14	2	1	98
cluster4	3468	219	9	3	3699
cluster5	30				30
cluster6	1042	210	17	6	1275
cluster7	706	33	2		741
cluster8	31949	694	15		32658
cluster9	264	19	1	2	286
cluster10	34	2	3		39
cluster11	67	33	10		110
cluster12	92	4	1		97
Grand Total	38430	1493	141	16	40080

5.8 Conclusions

As information technology has never stopped advancing, business processes are also getting more complicated. Deception and fraudulent actions also increase in complexity. Simple observation and traditional detection techniques can no longer recognize such activities. Companies are not only having to find new and innovative way to run their businesses, but they are facing more difficult tasks in control and monitoring their advanced business processes. Manual, quarterly and annually audit activities are no longer enough to protect the integrity of their financial information system. To keep up with technological advancement, businesses need to find new and innovative ways to control and monitor their processes. Technology and techniques from other discipline have been adopted and applied in business. Borrowed from other business fields, cluster analysis as an unsupervised learning algorithm is a good candidate for fraud and anomaly detection techniques. It makes use of the powerful information system, receives input from transaction systems, performs the analysis and provide the results to the internal auditor for the follow up or further investigation. Clustering can be used to group transactions so that different attention and efforts could be applied to each cluster so that it will reduce time and efforts required in the audit process.

This study examines the possibility of using clustering technique for auditing. Cluster analysis is applied to a data set from a major life insurance company in the United States. Group life insurance claims were grouped into clusters of claims. Claims with similar characteristics were grouped together. Clusters with small populations were flagged for further investigation.

Using cluster analysis to identify possible anomalies in the dataset of group life insurance, claims with suspicious characteristics are identified. These are the claims which have been in the systems for an extended period of time before approval and payment, or for which the insured is dead for a long period of time before a claim is submitted. In most cases, there are valid reasons to explain the anomalous characteristics. The possible reasons are for example;

- Required documents are missing,
- Beneficiaries cannot be contacted,
- Families are unaware of the insurance policy, or
- Cases are on hold pending investigation.

Though the reasons mentioned above are valid, it is undeniably that it worthwhile to take time to evaluate some of these cases. There is no real anomalous claim found from this dataset; however, the suspicious characteristics of these claims are of interest to the internal auditor.

Several parameters are available to researchers in order to perform cluster analysis. One may select different options from others. Moreover, the resulting groups may not be meaningful for further analysis. To clearly evaluate the results, researchers need helps from people with domain knowledge.

This study is a preliminary step toward applying the cluster analysis in the field of auditing. It shows that cluster analysis may be a useful technology for accounting.

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Chapter 6 Summary, conclusions, paths for further research, limitations

6.1 Summary of the results and implications

6.1.1 Cluster Analysis

Clustering as an unsupervised learning algorithm is a good candidate for fraud and anomaly detection. Without further investigation, there is no way to know for sure that a particular transaction is fraudulent. In other words, the transactions are not clearly identified as fraudulent or legitimate. It is often difficult to identify suspicious transactions. Clustering could be used to group transactions so that different attention and strategies could be applied to each different cluster. Outliers or anomalies could be identified.

This study examines the possibility of using the cluster analysis in auditing. The result shows that it is a useful technique for the accounting profession. It could be used in the area of automatic detection and continuous control and monitoring.

6.1.2 Anomaly detection using cluster analysis

Theoretically, outliers are a by-product of cluster analysis (Ester et al, 1996, Agrawal et al, 1998, Aggarwal et al, 1999). Regarding to the use of cluster analysis for anomaly detection; however, there is no study in the literature conducted using real world data. Several studies have been using synthetic data or seeded errors. Considering the nature of the technique, it is understandable why a researcher has to choose the type of data set. Anomaly detection is a subjective matter. What will be defined as anomaly? What will be the definition of outliers? These problems require the knowledge of domain experts. Because of the unsupervised nature of the cluster analysis, it is extremely difficult, if not impossible, to evaluate the results. Expert feedback is needed. With the

unique knowledge that the experts have about the domain, they will be able to provide the insight or information useful in the model building process.

Without the help from domain experts, researchers will have very difficult time to evaluate results. Therefore, using seeded errors seems to be reasonable choices.

6.2 Primary Contribution

Prior literature suggests many fraud detection techniques using data mining (Fanning et al, 1995, Green et al. 1997, Deshmukh et al, 1997, Fanning et al, 1998, Lin et al, 2003 Bakar et al, 2006). These models identify fraudulent firms using Accounting and Auditing Enforcement Releases (AAER) by the U.S. Securities and Exchange Commission or private datasets.

Because these models require fraud samples (i.e. fraud/none fraud firms) and/or use the data that is unique and not easily obtained, the models are not easily applicable in other real world settings. The main problem of inapplicability comes from the fact that it is extremely difficult, if not impossible, to identify fraudulent firms or transactions with total confidence. Therefore, if a fraud detection model can be developed that can sidestep this difficulty it will be very useful. Consequently, cluster analysis, an unsupervised learning algorithm, which does not require the knowledge of fraud/non fraud sample is a good candidate for fraud and anomaly detection.

This study examines the possibility of using clustering techniques for auditing. Cluster analysis is applied to three datasets, one dataset is from an international bank and two datasets are from a major life insurance company in the United States.

In the first setting, cluster analysis is used to uncover seven major types of transactions in transitory accounts. These major types or groups of transactions from branches were not previously known to the bank. Therefore, the clustering results provide new knowledge about transactions. This knowledge can possibly be used for creating new controls or detection rules in the transitory account system.

In the second setting, four anomaly detections techniques from cluster analysis are examined using a wire transfer dataset. There is no wire identified as possible anomaly by all four methods. Twenty-three and Eighty-one wire transfers are identified by three and two techniques respectively. No wire identified by all method can mean no real anomalous wires in the dataset. However, this explanation is highly unlikely. Because of underlining assumptions in each detection technique, different wire transfers are identified. Therefore, using different parameters, clustering techniques, and/or assumption can create significantly different results.

In the third setting, anomaly detection based on cluster analysis is applied to group life insurance claim. Clusters of claims with suspicious characteristics (i.e. being in the claim payment system for a long time before payment, and having a large interest payment) are identified as possible anomalies. Though these claims may not be real anomalies, they possess characteristics which are worth for internal audit to investigate further.

Overall, this study is only a preliminary step toward applying cluster analysis in the field of auditing. It shows that cluster analysis may be a useful audit technology. Automating fraud filtering can be of great value to audits.

Cluster analysis is a very promising technique that can be integrated into a schema of continuous system monitoring and assurance. Archival studies of data trends will reveal acceptable clusters and problematic ones, Experience, judgment, and monitoring procedures will evaluate these clusters, and categorize data. Progressively, clustering findings can be impounded into *a priori* processing filters and block transactions with bad weightings from processing. These filtered transactions will be routed to auditors (Vasarhelyi et al, 2010; Vasarhelyi et al, 1991) for review and subsequent action. Clustering results will provide an innovative and unique group of transactions for auditors to follow up. Therefore, traditional views for looking at results may not be enough.

From the introduction of the first application of continuous auditing in AT&T Bell Laboratories in 1989 (Vasarhelyi et al, 1991) to newer applications in a health organization and in an international bank (Vasarhelyi et al, 2010), audit tasks become increasingly automatic and more computer intensive. Newer and more advanced technology is needed.

6.3 Limitations

There are several options (i.e. distances or similarity measures, clustering algorithms) and/or parameters available for a researcher to choose when performing cluster analysis. Therefore, for the same dataset, one researcher may choose a different distance measurements and/or different clustering algorithm from another researcher. It does not necessarily mean that one is right and the other is wrong. While one may select different options from others, there is no one correct method. A technique/parameter may

be selected because it would make more sense/ produce a clearer/better interpretation of the results.

Cluster analysis is a very computationally intensive process. It can take unusual long time to run and provide results. To perform the analysis on a large dataset, a very powerful computer system is needed. Such a system can be extremely expensive. It can create problems for small companies wishing to try the technology. Pre-processing the dataset is also an alternative to speed up the analysis. Attributes can be transformed so that they take shorter time to be processed. Though the transformation can speed up the analysis, it can distort the meaning of the attributes. The transformed attributes may or may not have influences on how results will be interpreted. Therefore, results should be interpreted with care.

Cluster analysis will always produce grouping. However, a result may be statistically meaningful, while, at the same time, it does not provide any useful meaning. Given the nature of cluster analysis, to evaluate if results are useful requires the help from domain experts. It may or may not prove to be useful for the purpose that it is intended. The grouping may be useful or useless is a question of the application. Researchers need the expertise of people with domain knowledge for proper evaluation and interpretation of results. Without help and support from internal auditors, domain experts, good and useful clustering results will be difficult to obtain.

6.4 Future Research

This study, as an initial examination of the usage of clustering technology for auditing, is a good starting point. There are many possibilities for future research.

1. Cluster analysis can be used together with rule-based extractions in order to build the automatic fraud detection. There should be a study to combine the two methods or techniques together. Some possibilities are as follows:
    a. To use cluster analysis to create groups and, from the clustering results, to use rule-based extractions to create rules to detect possible anomaly in clusters.
    b. To use results from cluster analysis as one of the rule to detect anomalous transaction
    c. To use several rules to test or evaluate the dataset and use cluster analysis as an alternative technique to conclude the results from the rule.

2. Other algorithms and techniques in cluster analysis can also be tested. There are several clustering techniques available for the researcher to choose from. Some techniques may be appropriate for one dataset but not the other. Moreover, within one technique selected, there are a number of parameters to specify or to select. This study is only a preliminary trial of cluster analysis in the field of auditing. With the limitation on time and the availability of the technique in the software, only a number of techniques and parameter set have been selected. Therefore, other algorithms and techniques should also be examined in order to evaluate the suitability of this methodology in the field of auditing.

3. Other attributes and/or combinations of attributes can be used to investigate the usefulness of these techniques. In this study, because of data quality issues, only a few fields are recorded correctly or with care; hence they are considered as - unreliable. Domain experts know and accept the issues. They mention that they are working toward improving the quality of the data entered into the system. Upon the improved quality of data, with different data set, other attributes or combination of attributes can be used; therefore possibly greater varieties and specification of the clustering model can be examined.
4. Other data transformation techniques can be used to transform input attributes. Several attributes are transformed for the ease of processing. Transformation can affect results. Therefore, with different choices of techniques, different results will be produced.

Cluster analysis is a very promising area for accounting research. There are several possibilities that researchers should explore. With enough attention and support, this technology would become as popular as it has been in the field of marketing.

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