A Neural Network Approach to Estimating the Allowance for Bad Debt

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

by

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Virginia Commonwealth University
Richmond, Virginia
December 2011

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Acknowledgments

Pursuing my doctorate has been a dream of mine for many years. It has also been the single most difficult challenge I have ever undertaken. I could not have done it alone.

First, I have to offer my praise and worship to my Lord and Savior Jesus Christ. God gave me the ability to accomplish my goal. He also brought into my life people who have assisted me in accomplishing that goal. Even more important, God has given me the strength to keep pressing forward, even though it would have been easy to give up.

The Lord blessed me with the most wonderful wife any man could have asked to have by his side. More than any other person, I owe the most thanks to my precious wife Dottie. She has stood by me through all the ups and downs of the doctoral program and she has provided the emotional support I needed. Her name deserves to be on the degree as well as mine. She has had to sacrifice as much as I have to pursue my dream and she has never complained once.

I also have to thank my dear parents. They too have provided support in so many crucial ways. It is safe to say that without my parents' involvement, I would not have reached this milestone. They instilled in me the strength of character it took to make it through this program and they have never hesitated to provide assistance when I most desperately needed it.

I would be remiss however, if I did not acknowledge my maternal grandmother. I can remember at one time wishing for high school to be over so that I wouldn't have to study again. She was the one who talked sense in to me. My grandmother and I descended from hardworking, yet uneducated fishermen. She was fiercely proud to be the first person in her family to graduate high school and she preached the importance of education to me constantly. She made me realize that life would be much harder as an uneducated person than as an educated one. She lived to see me get my MBA from William and Mary and even though she is now with the Lord, I know her spirit has been with me on this journey as well.

I also wish to express my deepest gratitude to all of my dissertation committee members. You have no idea how much I appreciate the time and effort you spent in reviewing my work and providing suggestions. Each of you provided invaluable assistance. I especially want to thank my director, Dr. Ruth Epps. Dr. Epps has been a source of encouragement for me since my first semester at VCU. She has spent countless hours working with me in developing and refining my dissertation. She has taught me a tremendous amount about scholarly work. She has also become a treasured friend and mentor. She is a person who has taught me important life lessons in addition to everything else she has done. I also want to thank Dr. Andrews for the long hours we spent on the statistical part of this dissertation.

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ABSTRACT

The granting of credit is a necessary risk of doing business. If companies only accepted cash, sales would be negatively impacted. In a perfect world, all consumers would pay their bills when they become due. However, the fact is that some consumers do default on debt. Companies are willing to accept default risk because the value of defaults does not exceed the value of the additional sales generated. This creates an issue in regards to the valuation of uncollectible accounts. In order for a company to disclose the true value of its accounts receivable, it must establish an allowance for bad debt. Traditionally, companies estimate their bad debt expense and the related allowance for doubtful account by one of two methods: 1) As a percentage of total credit sales or 2) An aging of accounts receivable (that assesses a higher likely rate of default, the older the account becomes past due). By their very nature, these methods take into account only endogenous variables based on past experiences. For many years, the aforementioned methods of estimating bad debt were the only viable ways of determining the allowance for bad debts. However, with the explosion of technology and the easy availability of information, a more comprehensive method of determining bad debts seems appropriate. Neural network computer systems, which mimic some of the characteristics of the human brain, have been developed and may offer an alternative method for estimating the allowance for bad debt. These systems can predict what events may happen, analyze what did happen, and adjust the factor weights accordingly for the next set of event predictions. Thus, it is noteworthy to explore the use of neural networks to predict what a reasonable allowance for bad debt should be for an entity based on an array of interacting variables. Since, a neural network can incorporate both endogenous and exogenous variables one would expect to use such a system to develop a tool which gives a better estimation of the allowance for bad debt than the traditional approaches.

In the current study, the findings indicate that neural networks over the balance of the time are better predictors of a company's ending allowance for bad debt than regression. On a case by case basis, even when neural networks provide a less accurate estimate than regression, statistical analyses demonstrated the neural networks are a less volatile method and their predictions are less likely to result in a significant difference from actual allowance. Neither approach provides results that are exactly the same as the actual ending balance of the allowance for bad debt amount. Even though regression provides a more accurate estimate 45 percent of the time, this result is mitigated by two items: 1) On average, the absolute difference between actual and predicted is much lower when neural networks are used and 2) The standard deviation derived when using neural networks is only a third of the standard deviation derived from regression when applied to the absolute differences between the actual and predicted allowance.

CHAPTER I

Introduction

Almost everyone has an interest in credit scoring results. The credit grantors do not want to grant credit to someone who is going to default. Borrowers want an accurate assessment of their credit risk because interest rates and credit limits are based on such assessments. Stockholders are interested in credit because it affects the performance of their investment and lastly, auditors want to make sure that they issue an accurate audit opinion with regards to a company's liabilities.

Companies issue credit to consumers for numerous reasons. Credit allows individuals to purchase large-dollar items on a credit basis. Thus, instead of having to pay several thousand dollars now, they can take advantage of financing arrangements which allow them several months and even years to pay for the item. For many others, whose needs do not necessarily coincide with their paydays, credit constitutes a short-term loan. If companies did not offer such credit they would not generate as many sales. Further, longer-term credit provides an additional source of revenue for a company in the form of interest charged on account.

Additionally, Hall, et al. (2009) noted that financial credit risk assessment has gained a great deal of attention. Many different parties have an interest in credit risk assessment. Banks are interested because it helps them develop the risk of default and the interest rates it charges. Banking authorities are interested because it helps them to determine the overall strength of the banking system and its ability to handle adverse conditions.

At the beginning of the 2000, there were those who saw some warning signs regarding debt. Mustafa and Rahman (1999) examined the implications of the rapid rate of growth in consumer debt and attributed it to several factors: healthy employment, income trends, low inflation, aggressive and overly generous credit granting policies, and good consumer sentiment. According to Mustafa and Rahman (1999, p. 11) “massive inflows of foreign capital through the U.S. capital market depressed loan rates and contributed to credit expansion by making additional loan funds available at relatively lower costs.”

1.1 Research Motivation

Due to the poor state of the U.S. economy, consumer bankruptcies have increased at an alarming rate (Kapner, 2011, p. 3). One presumptive implication of these bankruptcies is they will impact consumer loans in a negative fashion. According to Malhotra and Malhotra (2003), consumer credits have risen from roughly $10 billion in 1946 to nearly $2 trillion by 2003. Currently, it stands at nearly $2.5 trillion as indicated by the latest statistics from the Federal Reserve. The size of these loans has made them a significant economic factor in the state of the economy.

Highlighting the severity of the debt situation, Mustafa and Rahman (1999) found that consumer debt has grown at a faster pace than disposable income. For the period 1983 to 1989, the total consumer debt increased 56 percent, which in real dollars, outpaced the 78 percent growth in disposable personal income. Additionally, in the period 1991 to 1997, revolving credit increased from $247 billion to $514 billion. This growth has continued unabated. The June 20, 2010 Federal Reserve Statistical Release reported revolving consumer debt at $826.5 billion. Mustafa and Rahman (1999, p. 15) concluded that “as long as consumers are optimistic about the future course of the economy, employment trends and price environment, they will continue to spend more.” Such a situation will encourage consumers to borrow more because they expect future income.

Adler and Waggoner (2010) noted that some creditors fear that regulators will favor consumers as the economy struggles to recover. In other words, some bad debt accounts could be eliminated by the government, thus forcing creditors to absorb the losses. Additionally, Adler and Waggoner report that as of the beginning of 2010 the unemployment rate was 10.2 percent, the worst that it has been since April 1983. Nevertheless, Adler and Waggoner (2010) indicate that one way creditors are coping with these adverse conditions is to focus on technologies which enable them to make better credit granting decisions.

Hand and Henley (1997) stated that it is important for a credit scoring system to reach a real time decision. Otherwise, potential borrowers will take their business elsewhere. Methods such as regression, nearest neighbor, and tree-based methods, as well as, neural networks have the ability to reach decisions. Arguably, neural networks are best at automatically and independently classifying data. They are “well suited to situations where we have a poor understanding of that data structure” (Hand and Henley, 1997, p. 12).

According to Green and Choi (1997, p. 16) an ANN (artificial neural network) “builds a classification model by finding any existing patterns of input data.” The strengths of an ANN as a classification tool include their ability to adapt, their ability to generalize, and the fact that they do not require rigid assumptions. Overall, ANNs are better able to avoid the noise created by large amounts of data and derive an analytical behavior pattern. Analytical tools such as financial ratios are quite useful, but they do not tell a story that is as comprehensive as an ANN. Companies have to estimate the number of accounts that will default. Since no one can predict the future, the goals of any system to estimate this amount should be ones that will provide the most accurate and reliable results. It should be noted that the allowance for bad debt must be estimated using the methods outlined by Generally Accepted Accounting Principles (GAAP).

The results of this or any other study which attempts to make a more reliable estimate of the balance in the allowance account does not change GAAP. A company has the latitude to adjust the allowance for bad debt to any number it chooses. The methods outlined by GAAP mean that a company has to follow a particular methodology in estimating the allowance for bad debt, but the items incorporated into those calculations are very subjective. Ideally, companies should make a good faith effort to derive the most reliable estimates possible. However, given the subjective nature of the process, ANNs are beneficial for purposes of verifying the reliability of management estimates.

1.1 Research Goals and Objectives

1.2.1 Problem Statement

The ultimate goal of this study is to derive an actual working technique for predicting bad debt. This will take the form of an ANN. Once a set of relevant variables has been identified an artifact can be designed to predict the amount of bad debt incurred. It may take several iterations; however, the final artifact should be one which is readily usable because the model has demonstrated results consistent with the company's actual book value results.

Since the allowance for bad debt is an estimate, management may use the process of estimating bad debt as a means to manipulate earnings. In order to curtail the abuse of bad debt as a mechanism for adjusting overall net income, several benchmarks have been developed to measure the accuracy of the allowance estimation. This study attempts to demonstrate that a ANN approach will classify (i.e. determine whether the bad debt provision is underestimated, equal to, or overestimated) and predict a bad debt allowance amount more closely aligned with the bad debt expense incurred during the fiscal period than traditional management approaches to estimating the allowance. The current study will employ ANNs in combination with conventional statistical tools such as cluster analysis and regression analysis to see which method is the most accurate for making bad debt estimates. The focus of this study is to develop an artifact (i.e. ANN) which is adaptable to a changing economic environment.

ANNs are built upon the notion of data mining. A human being can observe a set of variables or circumstances, but only on a limited basis. A person cannot process hundreds of thousands of data variables. It is beyond human capacity. However, an ANN is able to observe a vast number of variables and even though the data is massive, the ANN is able to mimic the human brain with regards to classifying sets of data on a large scale. Costea and Nastac (2005) believe predictive data mining has two aims. The first aim is to uncover hidden relationships and patterns in the data. The second aim is to construct usable prediction models. The prediction model consists of classification models which are able to predict the outcomes of new cases against actual results.

Hand and Henley (1997) noted that in the past, data sets were relatively small, numerical and clean. This enabled the use of statistics to derive relatively straightforward answers. However, this is no longer the case as modern databases may contain billion records. To take advantage of the massive amounts of information, data mining is a technique which is now quite feasible and widely accepted.

Classification, in this study, pertains to classifying bad debt allowances as adequate, inadequate, or overstated. Kim, et al. (1993, p. 167) stated that "the various approaches to the classification problem can be grouped into two paradigms: statistical approaches based on statistical assumptions and mathematical processes, and human knowledge processing approaches which rely on artificial intelligence techniques." According to Kim, et al. (1993), ANNs fall into the category of artificial intelligence.

This study seeks to contribute to the existing literature by demonstrating that ANNs can be used to improve the accuracy of credit granting decisions, which in turn can reduce bad debt write offs. The minimization of bad debt write-offs is beneficial to everyone. For businesses, it can save money through lower debt default rates. For customers, it can reduce interest rates. Other studies have tried to develop a credit granting mechanism using ANNs. However the aim of this study is to demonstrate the accuracy of ANN prediction versus the conventional methods of granting credit and determining the provision for bad debt.

1.2.2 Research Question

The objective of this study is to determine whether the utilization of ANNs is a valid and useful mechanism for analyzing credit risk and estimating the allowance for bad debt. Zurada and Kunene (2010, p. 1) note that "accurately evaluating the credit risk posed by financial institutions loan granting decisions cannot be underestimated." They note this is clearly demonstrated by the large credit defaults in recent years. In addition, Zurada and Kunene (2010) also note that credit scoring models are not new phenomena. They have been used for decades to group customers into two categories: good credit and bad credit. A good credit customer is likely to repay the debt whereas a bad credit customer is likely to default. An analysis of bad debt can provide, indirectly, an indication of whether or not a company's credit granting policies are proper. Zurada and Kunene (2010, p. 2) underscore the importance of a good credit scoring model: "even a 1 percent improvement in the accuracy of a credit scoring model can save millions of dollars in a large loan portfolio."

The best method for analyzing bad debt and estimating an allowance for bad debt depends on data structure, the characteristics of the data, the ability to classify the data, and the objectives of classification. Even though classification is crucial, the quickness of classification, the promptness in which classification can be revised, and the ease with which the classification method and the results can be understood, are important. This study posits that with the utilization of neutral networks and their capability to handle large quantities of data through various iterations, an estimation model for the allowance of bad debt can be developed which would possess the characteristics of the quickness of classification, the promptness in which classification can be revised, and the ease with which the classification method and the results can be understood. The artifact produced by this study may provide a tool for unbiased evaluation as to the reliability of management estimates of bad debt.

While this study employs independent variables based on prior literature, rather than actual surveys, the artifact should demonstrate a movement toward increased accuracy in determining the allowance for bad debt. Further, the methodology used to estimate the allowance for bad debt should be understandable. Thus, allowing companies to design their own artifact using their own particular variables.

1.3 Bad Debt Allowance

1.3.1 Methods of Estimating the Allowance for Bad Debt

The allowance method for bad debt can be estimated in three different ways according to Generally Accepted Accounting Principles (GAAP). The first method is an Income Statement approach. Under this approach, a company estimates the percentage of its credit sales which will ultimately prove uncollectible. The second and third methods of estimating bad debt are Balance Sheet approaches. Unlike the Income Statement approach, which simply records an expense without consideration of the existing allowance for bad debts, the Balance Sheet approach adjusts the amount estimated to be uncollectible based upon the amount of bad debt expense. This uncollectible amount may be based on an aging of receivables or an estimate of the amount of overall accounts receivable which are expected to be uncollectible. There is little or no evidence to determine the details of how an individual company arrives at its estimate for bad debts. All that is known is that: 1) the amount should be based on GAAP and 2) the amount will involve estimates and subjective judgment.

1.3.2 The Artifact

In the past, many of the criteria used in decision processes by human beings were not quantifiable. Presently, a multitude of data can be extrapolated and used in real-time to make 'automated' estimates of bad debt expense and other accounts previously subject to human estimates. Furthermore, any number of variables may provide explanatory power. It is therefore quite within the realm of possibility to reduce inaccurate bad debt estimates using advanced technologies such as ANNs.

The primary objective of this research is to develop an artifact useful for predictive purposes. Ultimately, the value of this research will be judged by the model's accuracy, which should provide better estimations of the allowance for bad debt, than previously obtained using conventional methods. The primary method for evaluating this 'artifact' will be to apply the results obtained from this model compared to a method outlined by Riley and Pasewark (2009) for assessing the accuracy of the allowance for bad debts account.

Gulliver (2009) noted that bad debt allowances can be discovered through an examination of the bad debt expense and the allowance for bad debt accounts. The fact that the relationship between bad debt expense and allowance for bad debt can be used as an indicator of accuracy provides a method for researchers to compare different methods.

Additionally, the ratio of the allowance for bad debt to bad debt write offs method indicates how adequately the allowance accommodated subsequent write-offs., Riley and Pasewark (2009,

p. 41) state that if the ratio is low, it means that the allowance for bad debt is underestimated, while a high ratio indicates that too much allowance for bad debt was accumulated. In this case, the standard deviation is a measure of volatility. A small standard deviation indicates low volatility while a higher standard deviation indicates higher volatility.

The artifact resulting from this study will have a two-fold purpose. First, it will seek to accurately classify companies into two groups, those that underestimate bad debt and those that overestimate bad debt. Second, the artifact will make a numerical prediction of the bad debt which will be incurred.

CHAPTER II

Literature Review

2.1 Determinants in Estimating Allowance for Bad Debt

One could make a valid argument to include any number of variables in a new credit rating system. Angelini, et al. (2008) noted that contemporary credit scoring models are not necessarily free of mistakes. It should be noted that market risk and credit risk are not the same things. Banks have primarily focused on market risk, which is concerned with locking in an investment at a rate that is lower than future rates. Such an investment would keep the bank from capitalizing on the higher investment interest rate. A market risk model therefore focuses on the near-term. As Angelini, et al. (2008) note, credit risk requires a larger set of historical data and often the needed historical data is not present. In addition, many credit risk models do not accurately specify the variables to examine.

According to West (2000), the magnitude of installment credit, home mortgages, car loans, and credit card debt has rapidly increased over the 1980's and 1990's. Credit scoring models have gained widespread acceptance because they improve cash flow and credit collections. Such models facilitate faster decision making regarding credit, better monitoring of existing accounts, and the prioritization of collection efforts.

Gulliver (2009) examined the connection between aggressive accounting and poor earnings quality. Among some of the signs associated with aggressive accounting, which affects accounts receivable and margins are: revenue recognition without earnings; capitalizing period expenses; manipulation of reserves and accounting for deferred taxes.

2.1.1 Macroeconomic

Exogenous variables should be considered when estimating the allowance for bad debt. A narrow, inward-based view ignores many compounding factors. According to Mustafa and Rahman (1999, p. 12), "the data on personal bankruptcies and delinquencies indicate that some consumers have become overburdened with debt." Mustafa and Rahman used the following factors to examine consumer debt: total real consumer spending to real disposable personal income, real durable goods consumption expenditures to real disposable personal income, real nondurable consumption expenditures to real disposable personal income, real personal expenditures on automobiles to real disposable personal income, real total consumer debt, real total installment credit, and real automobile loans. Their data was obtained from the 1999 *Economic Report of the President.*

These variables pertain to the economy as a whole and not to any individual company. Some of the variables which can be included in this category include annual consumer bankruptcies (by amount and by type, which is an indication of what a company can expect based on the economy), the rate of inflation (higher inflation equals less disposable income in real dollars, which could affect the ability to pay loans with pre-set payment amounts), the rate of consumer spending (indicates whether sales are high/low based on the economy), the unemployment rate (if one is earning no income, one can't repay debt), GDP (i.e., Gross Domestic Product: an approximation of the market values of goods produced in the economy), and average personal income (an indication of how much people have to spend as well as their ability to repay debts). Each of these variables could be logically associated with debt defaults and will be considered for inclusion in developing the artifact.

Pesaran, et al. (2005) indicated that the following macroeconomic variables are of importance in risk forecasting: inflation, interest rates, money balances, and foreign exchange rates. Other databases, such as those provided by the American Bankruptcy Institute (annual consumer bankruptcies by district and chapter), the U.S. Bureau of Labor Statistics (inflation, spending, and unemployment), and the U.S. Bureau of Economic Analysis (GDP and personal income) are potential sources of numerous macroeconomic variables. Other endogenous and exogenous variables which merit consideration are: growth rate in sales, accounts receivable/sales ratio, instances of greater than 10 percent increase in accounts receivable, inflation, prevailing market interest rates, foreign exchange rates, employment rates, salary trends, inflation rates, total real consumer spending to real disposable personal income, real durable goods consumption expenditures to real disposable personal income, real nondurable consumption expenditures to real disposable personal income real total consumer debt, real total installment credit, bankruptcy rates and loan loss reserves/gross loans.

2.1.2 Firm Specific

Firm specific variables relate to the firm and its year-to-year performance. These variables include growth rates in credit sales and/or loans (more loans require greater evaluation, added administration, and more risks), accounts receivable to total sales (an indication of the company's reliance on credit and related credit policies), change in accounts receivable to total sales (a large change could indicate a shift in credit policies and exposure to more risks), and changes in inventory (an indication of how much the company is selling/not selling).

2.1.3 Fraud Specific

Fraud specific variables are items subject to earnings manipulation and misstatement. The variables in this category include percentage of board comprised of outside directors (decreases fraud because these individuals are not involved in the day-today operations of the business), existence of an audit committee (indication that oversight exists), existence of a profit sharing plan (creates an incentive to overstate net income by failing to record adequate allowance for bad debt), size of independent auditor firm (a larger firm is more likely to catch mistakes), and top executive turnover (indication that there could possibly be internal problems within a company). While these variables are not included in this study, for an independent auditor working for a client, such variables would be known and could be incorporated into the model.

Fanning and Cogger (1998) focused on publicly available information (from COMPUSTAT). Their goal was to predict fraudulent financial statements. In order to do so, Fanning and Cogger (1998) used AutoNet, which is an ANN used to predict fraudulent financial statements. They stated that sales, accounts receivable, allowance for bad debt, and inventories are the financial variables most susceptible to management manipulation. Initially, they selected 20 variables which should or could be related to eventual financial fraud. The ANN then selected eight (8) variables which, combined, produced statistically relevant results. Among the variables Fanning and Cogger (1998) selected were: board size, percentage of the board comprised of outside directors, same individual serving as both chief executive officer and chairperson of the board of directors, audit committee exists, auditor is not a big six firm, existence of a profit-sharing plan, financial distress (as indicated by Z score), growth rate, chief financial officer turnover within the last three years, president of the company serving as treasurer, pending litigation, last in, first out (LIFO) inventory method used, accounts receivable to sales ratio, inventory to sales ratio, net property plant and equipment to total assets ratio, debt to equity ratio, sales to total assets ratio, greater than 10 percent increase in accounts receivable, and gross margin.

Hall, et al. (2009) concluded that ANNs are advantageous because with minimal error they are able to accurately predict default probabilities. Hall, et al. (2009) also identified the stock price index as a significant independent variable.

2.1.4 Loan Specific

Loan specific variables are variables a firm would consider when granting credit. These variables include total installment credit (amount of loans which consist of fixed payments), stock price index (indication of better investment options), changes in stock price (an indication whether analysts foresee problems with the way the company is doing business), and foreign exchange rates (ease or difficulty with which foreign funds impact the U.S market, which can influence interest rates), and U.S. bond rates.

Additionally, the following bad debt/ bankruptcy variables are used in the Quek, et al. (2009) study. The study is predicated upon the presumption that banks nearing bankruptcy will demonstrate a distinct set of financial characteristics. They used the following variables in their model: average total equity capital/average total assets, total interest income – interest expense/average total assets, net income after tax/average total equity capital, and average loan loss provision/average total loans.

2. 2 Artificial Neural Networks

One of the first researchers to propose using ANNs to determine corporate bankruptcies was Atiya (2001). These ANNs are particularly important to the banking industry for determining interest rates on loans and the overall value (i.e., creditworthiness) of a bank's loan portfolio. Atiya (2001) noted that the application of ANNs to bankruptcy prediction did not begin until 1990. Overall, ANNs perform better than conventional techniques, because these networks employ a non-linear approach as opposed to a linear approach. Atiya (2001) indicates that while a firm's financial ratios are not necessarily wrong to use in the development of ANNs, external variables should be considered as well. Among these variables are: stock price to cash flow ratio, the rate of change of stock price, the rate of change of cash flow per share and stock price volatility. Atiya (2001) notes that since ANNs have demonstrated the best performance of any model, the goal should not be to keep proving they are superior, instead the goal should be to improve the performance of existing ANNs (either through better training methods or better architecture) and identifying better input variables.

If auditors are to be effective in auditing different clients, they must be capable of handling knowledge transfer. Thibodeau (2003) defined three conditions which must be met for knowledge transfer to happen. First, there must be a common element to the task (i.e., loan evaluation), second, there must be a content of knowledge (i.e., the base task is understood by the auditor and maintained in memory), and third, there must exist an organization of knowledge (i.e., general knowledge applicable to the specific task isn't intermingled with other knowledge, which would interfere with the task at hand). An ANN can incorporate these three conditions needed for the transfer of knowledge.

O'Leary (2009) believes that the manner in which firms are adopting new technologies is changing. Typically, new technology tools are added to an existing technology infrastructure. Often, new technologies gradually become embedded in other technologies. However, artificial intelligence tends to evolve along different lines. These technologies have the capacity to separate from their original component and become a stand-alone mechanism.

Costea and Nastac (2005, p. 230) stated that "the main advantages of neural network approaches for classification over the traditional approaches are that ANNs are free of any distributional assumptions, are universal approximations, eliminate problems with inter-correlated data, and provide a mapping function from the input to the outputs without any *a priori* knowledge about the function form." They also note backwards propagation (BP) is the most popular ANN method. However, they indicate there are challenges in using backwards propagation. First, as the complexity of the event being analyzed increases, the training time increases non-linearly. Second, if backwards propagation is applied to a fairly simple problem, the training process may take longer. Other problems with backwards propagation involve the manipulation of outliers and reduced generalization for large solution spaces. Often, ANNs which use BP, rely heavily on initial starting values. As a way to reduce these problems Costea and Nastac (2005, p. 231) suggest preprocessing the input data. This can be accomplished by examining individual outputs to obtain the "same dimensionality of the input dataset." Another way is to "apply a transformation on the whole input data set at once, possibly obtaining a different dataset dimensionality" (Costea and Nastac, p. 231).

Wright and Willingham (1997) discussed the theory of computational modeling. Computational modeling involves tasks which require "semi-structured judgment" (p. 99) and requires a great deal of "task-specific knowledge" (p. 100). Anderson (1987) discussed the adaptive control of thought (ACT) theory of skill acquisition. According to Anderson (1987, p. 192), this theory proposes that “cognitive skills are encoded by a set of productions, which are organized according to a hierarchal goal structure.” In new domains, people apply weak problem-solving steps to the declarative knowledge they have about the domain. Thus, accountants should view ANNs as an opportunity to demonstrate their expertise, not something to fear.

The evolution of technology has developed to a point where it should be viewed as a potentially invaluable tool. Baldwin, et al. (2006) stated that the usage of artificial intelligence in accounting has consisted primarily of expert systems. However, these expert systems have not proven as useful as once expected. Accounting and artificial intelligence have a 25 year history. Using an expert system would be acceptable in accounting if conditions remained static and no ambiguity existed, but that is rarely the case. Hence, something more robust is needed to determine credit policies. Thus, the use of an ANN is an appropriate tool to explore the determination of credit policies.

While, not the goal of this study, the goal of Ragothaman, et al. (2008) was to identify common characteristics shared by firms with earnings restatements. Once identified, those characteristics could be used to develop an ANN capable of predicting future restatements. Such an ANN would serve to forewarn interested parties such as investors, auditors, and analysts. Similarly, an ANN could also be designed which provides warnings regarding ill-advised credit granting decisions. According to Ragothaman, et al. (2008, p. 98): “Neural networks are mathematical models that are based on the architecture of the human brain. Neural networks consist of nodes in multiple layers; these nodes are sometimes referred to as processing elements. The weight associated with a particular node denotes the degree of influence it has on other nodes. A series of input nodes from the base layer, and the top layer, or output layer, can have one or more nodes. There can be one or more hidden layers, where most of the learning takes place, between the output and input layers. The output of a node is equal to the weighted sum of input values after transformation by a transfer function."

Humans can only process a limited amount of information before succumbing to information overload. ANNs, however, do not suffer from information overload. According to Ramamoorti and Traver (1998, p. 2), ANNs offer "tremendous pattern recognition capabilities" and can focus on the financial and operating data of a company and indicate areas where hazards may exist. Swingler (1996) noted that ANNs focus on input-output pairs in order to determine if generalizable patterns exist. Thus, in essence, the function of an ANN is to act as an extension of the human brain. Experts can surmise where patterns may exist in data, but they have no way of being able to process all the information. Consequently, an ANN is very beneficial because it can function similarly to the human brain *and* in addition, handle tremendous amounts of data.

An ANN artifact can enable a non-expert to arrive at correct conclusions, because the ANN has already been programmed with a pre-existing set of relationships and how to assess those relationships. In addition, ANNs are able to 'learn' because they can adjust the weights assigned to certain relationships based on observed historical patterns. It does not employ static relationships. Therefore, from a hypothetical perspective, a non-expert could use a well-designed ANN to arrive at proper conclusions, even if the ANN was designed years ago. From a practical perspective, an ANN has the potential to aide a company wishing to assess any and all potentially relevant variables.

ANNs use two parameters: learning rate and momentum. These parameters help determine how an ANN will adjust the connection weights of the parameters placed in the model. Costea and Nastac (2005) find ANNs to be more robust and reliable than conventional analytical procedures. The study examines traditional gradient-descent training algorithms and how to train ANNs. The first step is to select variables and assign an initial set of weights. Secondly, after several iterations, these weights are re-examined and adjusted. The best set of weights for predictive accuracy is chosen by the ANN after each successive experiment.

Ragothaman, et al. (2008) indicated that ANNs are capable of both supervised and unsupervised learning. Under the unsupervised learning model, the network is presented with a group of input variables, but no output variables. As a result, the ANN attempts to develop an algorithm which will classify the different inputs. This approach is similar to multivariate analysis. Under the supervised learning model, the ANN is given the input variables along with actual output variables. This allows the ANN to calculate weights for each variable (i.e., node). This process is iterative. The ANN is run repeatedly in an effort to better specify the importance of each input variable. Ragothaman, et al. (2008) explains that ANNs are subjected to repeat testing until an acceptable level of accuracy is achieved (80 to 90 percent). It is at this junction that the ANN is placed into an operative mode to classify new data.

Ragothaman, et al. (2008) noted the rate of financial restatements have increased at an ever-growing rate. Financial restatements increased from 92 restatements in 1997 to 225 in 2002, and to 1,295 in 2005. Ragothaman, et al., suggest that such restatements could have been predicted if a trained ANN were in place. Consequently, they compare the probability of misstatement calculated by an ANN (which demonstrated the best results) with the results produced by 'traditional' models including multiple discriminate analysis and logit analysis.

2.2.1 Knowledge and Understanding of Problem:

Rammamoorti and Traver (1998) noted cognitive psychology has demonstrated experts in certain fields are able to recognize patterns and relationships in data. However, it takes a computer, or other processing device with more memory than the human brain to fully analyze the patterns and relationships in large amounts of data.

Wright and Willingham (1997) indicated that little research has been performed in the area of auditor evaluation of loan portfolios. They noted the manner in which auditors classify loans as doubtful is imprecise. There is very little consensus among auditors regarding the evaluation of loan collectability. Usually, a loan-loss percentage range is used, with the ranges being 1-10 percent, 11-15 percent, 16-24 percent, 25-34 percent, 35-44 percent, 45-59 percent, 60-74 percent, and 75-100 percent. Wright and Willingham (1997, p. 105), stated auditors examine loan information "in a top-down (theory-driven) fashion." Auditors use their knowledge and education to evaluate loan collectability using variables such as: strength of and access to collateral, borrower's financial condition, expected degree of short-term liquidity, expected degree of business risk, and expected degree of financial risk.

Chan and Kroese (2010) examined the possibility of using computer generated algorithms to assess loan portfolios. They consider the problem of accurately measuring the credit risk of a portfolio consisting of loans, bonds and other financial assets. One particular performance measure of interest is the probability of large portfolio losses over a fixed time horizon.

Kuldeep and Bhattacharya (2006) stated that credit ratings are tools companies use to improve their image. A good credit rating also allows a company to go public and to borrow funds at lower costs. As a result, Kuldeep and Bhattacharya (2006, p. 217) concluded: "any reliable model to forecast credit ratings of companies would obviously carry great utility both for the general public and the companies themselves." The general public benefit because they are able to identify safe investment opportunities while the companies benefit because they are able to achieve certain financial goals.

In its simplest form, a credit rating model uses only two categories: good and bad. It does not analyze past results. Vellido, et al. (1999) noted credit scoring (i.e., classifying individuals into 'good' or 'bad' classes) should be distinguished from 'behavioral' or 'performance' scoring which only attempts to analyze behavior of individuals only after credit has been granted. Vellido, et al. (1999) stated in regards to retail credit, very little research has been performed in this area. The reason for this is that retailers are reluctant to adopt new technologies unless substantial benefits can be demonstrated. Nevertheless, many companies have adopted such technologies.

Since an ANN learns as it is presented more information, and since a computer is able to make faster and stronger statistical inferences than the human brain, applying a rational explanation to an ANN's decision can be very difficult, if not impossible. The main focus is that it makes accurate predictions. One could argue that the Equal Credit Act should prohibit the usage of ANNs the credit granting process; however, it has not deterred retailers. Companies such as Certegy, which provide information to retailers as to whether or not to accept a check have created a great deal of controversy. The origin of Certegy's system can be traced to United States Patent 6,647,376, which clearly shows the system employs ANN architecture.

Consequently, as noted above, Certegy provides little, if any information to consumers regarding their credit decision. Certegy only indicates that some guideline was not met by the consumer. Certegy cannot fully explain the final decisions reached by its ANN system. Thus, since no judicial injunction has been issued against Certegy and its use of an ANN, it can be inferred that usage of ANNs in credit granting is feasible (see Appendix A).

2.2.2 The Design Artifact which will accomplish the Solution

Morris and Empson (1998) noted that research has lagged behind practice as practitioners have begun to understand the value of knowledge in terms of its uniqueness and potential for competitive advantage. Morris and Empson (1998, p. 612) do not argue that individuals within a professional service firm (PSF) are unimportant. However, in order for a PSF to truly derive maximum benefit from its knowledge, the organization must be seen as a repository of knowledge "through routines and procedures." Not all PSFs learn at the same rates or with the same efficiency. Consequently, a PSF would be well-advised to develop a system of codifying knowledge so that knowledge can be more readily transferred between individuals within an organization.

Credit models used in the past and in many instances today are flawed. West (2000) stated these credit scoring models are based on linear discriminant analysis. West (2000, p. 1132) noted such a method is flawed because "the covariance matrices of the good and bad credit classes are not likely to be equal." In addition, the credit data is usually not normally distributed.

The issue of credit is ultimately a risk assessment issue. According to Ramamoorti and Traver (1998), the issue is distinguishing between business decisions which are risky from those which are less risky. Ramamoorti and Traver (1998) noted while the human brain is able to discern patterns, it is unable to process the massive amounts of data. Thus, the speed, accuracy, and capability of computers to handle massive amounts of data provide researchers with a valuation tool for analyzing credit risk.

According to Pesaran, et al. (2005) credit risk modeling is concerned firstly, with the properties at the tail end of a normally distributed loss distribution for a given portfolio of credit assets such as loans or bonds. Secondly, the model attempts to provide quantitative analysis of the extent to which the loss distribution varies with changes to firm/industry-specific, national, and global risk factors. The current issue can be viewed from the perspective of individual loans or the loan portfolio as a whole. The results of the research performed by Aragones, et al. (2007, p. 118) indicated options markets are a good indicator of market volatility as indicated by ANN accuracy. Aragones, et al. (2007) reached the conclusion that ANNs are excellent tools because they "do not rely on strong assumptions about the distribution of the underlying variables and, therefore, can overcome some of the limitations of more restrictive traditional volatility estimation models." Perhaps, the greatest advantage of using ANNs is their ability to adjust for changes very rapidly.

Coakley and Brown (1999) indicate that ANNs are concurrent. The recurrent function of ANNs means that inputs are re-evaluated as new output data is acquired. It is similar to using lagged variables and a moving average factor in forecasting. Such a model is much better equipped to handle major economy-wide changes. Additionally, Coakley and Brown (1999) note, if the properties of the data and the distributional assumptions required by a parametric model differ, then this is an indication of non-linearity. If non-linearity exists in the data, then use of an ANN is warranted.

Kirkland (2006) stated that dashboards can be designed to provide alerts to managers. Since accounts receivable and default rates on credit are items that managers would want to assess the design of executive dashboards would presumably incorporate alerts relating to those issues. If the dashboard is based on an effective ANN, then the demand for excessive amounts of information could be reduced (Kirkland, 2006).

Lastly, the friendliness of the current technological environment to obtaining and manipulating data must be emphasized. Rowbottom and Lymer's (2009) research indicate most users prefer companies to report financial data through excel spreadsheets. Private shareholders at least want the data in HTML format so they can manipulate the data and analysts (who have refined search methods) prefer financial information in PDF form. Dashboards, another form of a computerized decision aid, were once only limited to providing internally generated information to internal users. However, in today's climate, a programmer could easily design an ANN, or even a dashboard to retrieve information that is externally generated. This is pertinent to the current research as cited by Kirkland (2006, p. 2), the "heart of any dashboard" includes items such as "revenue forecasts" and "accounts receivable," both of which have a great effect on allowance for bad debt.

2.3 Estimating the Allowance for Bad Debt - Accounting Discipline-Based Approach

McNichols and Wilson (1988) used bad debts and the allowance for bad debts as proxies for overall earnings management. Consistent with expectations, they found bad debt allowance is manipulated up or down to meet earnings expectations. In essence, bad debt expense is a discretionary component of earnings and valuation.

Jackson and Liu (2007) had similar findings to McNichols and Wilson (1988). Accordingly, bad debt expense and the allowance for bad debt are manipulated in response to analyst forecasts. Jackson and Liu (2007) found evidence which showed companies use bad debt expense and the related allowance for bad debt as a major area of earnings management because assets can be consistently undervalued year after year without drawing much attention to their movement. Jackson and Liu (2007) found many companies have large allowances for bad debt reserves, which enables them to absorb very large default rates without a related drop in income.

Kuldeep and Bhattacharya (2006) noted ANN structures should be "pyramidal." For example, the input layer may contain 25 neurons, 16 neurons in its hidden layer, and 6 neurons in its output layer. In addition two key factors, learning rate and momentum, must be considered in arriving at an estimate for the dependent variable. The dependent variable in the current study will be the allowance for bad debt.

Simply put, learning rate pertains to the initial weights assigned to independent variable coefficients. If the coefficients are set initially low, the ANN will act from the presumption that those independent variables have little influence. Conversely, if the coefficients are set high, the ANN will assume the respective independent variables carry significant influence. Consequently, in terms of 'learning,' the ANN will learn faster the sooner it has to consider the impact of a particular variable. If the weight assigned to the variable is initially low, the learning rate will be slower. If the weight assigned to the variable is high, the sooner the ANN will have to analyze the variable, thus the learning rate is faster. There is a trade-off however. If one chooses to set initial weights relatively high, it could bias the manner in which the ANN analyzes the data. If the weights are set to very small numbers, the ANN is forced to analyze each variable with no predefined bias. Thus, while low weights may lead to a slower learning rate, it has the benefit of forcing the ANN to consider each independent variable equally.

As the ANN analyzes the independent variables, it will go through many iterations of analysis. Momentum refers to how many iterations an ANN will perform on the data before reaching a conclusion. If momentum is set high, then the ANN will perform less iteration before reaching its conclusion. If momentum is set low, the ANN will perform more iteration before reaching its conclusion. A lower momentum level may be chosen in order to achieve greater accuracy because it entails more analysis on the part of the ANN. However, a balance must be found. More iteration does not necessarily guarantee better results and less iteration does not necessarily entail poorer results. Given that ANNs are, in a way, analogous to the human brain, there is a risk of both over analyzing and under analyzing data.

Kuldeep and Bhattacharya (2006) reached several conclusions about ANNs. First, while ANNs are good classifiers of items, they tend to perform better in the short run than in the long run. Kuldeep and Bhattacharya (2006) attribute this phenomenon to the difficulty associated with incorporating the element of time into the ANN. Second, Kuldeep and Bhattacharya (2006) acknowledge that ANNs are better at predicting bankruptcy than other models because they are better equipped to deal with missing variables, multi co-linearity, and outliers. Third, they feel that ANNs would benefit if macroeconomic variables such as interest rates were incorporated into the model.

Kuldeep and Bhattacharya (2006) constructed two models, one was an ANN model and the other was a linear discriminant analysis model to predict the credit-worthiness of individual companies. Each model was based on data from 92 companies and was validated on 37 companies. The goal was to classify each company properly into 6 different investment grades (which were already assigned by Moody's). Their results showed the ANN is a better predictor and they were able to accurately classify 79 percent of the 37 companies from the holdout sample, while the linear discriminant analysis model was only able to accurately classify 33 percent of the 37 companies.

Kaastra and Boyd (1996) view network training as an iterative process. For example, if an original model is developed and compared to actual results; it is not likely the predicted values will be a close approximation. However, as the model is exposed to more and more years' worth of results, it will learn and the model will be improved.

Once the designer of the ANN is satisfied that the 'artifact' is producing accurate results, it can be placed into operation. If it has been designed well, it should continue to learn. Penharkar (2002) examined non-binary genetic algorithms to determine how an ANN would change the manner in which the network learns connection weights under different structural designs and data distributions. He found that data distribution characteristics, size, and additive noise have an impact on the manner in which ANNs learn, their reliability, and ultimately their predictive accuracy

2.3.1 Neural Network Paradigms

While using an ANN to grant credit would not likely impact lower management, it could have some potentially negative effects. For example, credit decisions that were once made regionally, would now be made nationally. Perhaps, the decision criterion used by companies such as Certegy represents a national perspective when a regional one would be better. An example of this could be seen at the local branch of a bank. It is the job of the manager of a local branch to become familiar with people in the local community. This relates to the marketing function of the bank. In many instances, the branch manager may know information about an individual, which makes them a good loan risk. However, if that decision is taken out of their hands, and placed into the hands of a national decision-making system, the bank may decline to lend money to otherwise credit-worthy customers.

Kaastra and Boyd (1996) stated an ANN can be constructed in an “infinite” number of ways. As a result, the contributions and findings of this study are highly unlikely to match the exact findings of any similar study. The two paradigms outlined by Kaastra and Boyd (1996) are neurodynamics (the number of inputs used and how they are combined) and architecture (the number of neurons in the ANN, which includes the variables selected and the form of the output).

2.3.2 Traditional Approach – Percent of Sales

Riley and Pasewark (2009) described the methods currently used by auditors to estimate the allowance for bad debt. The most frequently used method is the aging of accounts receivable. This method estimates bad debt at specific times; however, the disadvantage of this method is that it ignores the accuracy of past estimates using the method. While not a completely inaccurate method, the aging of receivables is in all likelihood not the best method, because the method omits relevant data. Riley and Pasewark (2009, p. 44) stated that “it is crucial for accounting professionals to use all available tools to understand the effectiveness of past estimates and maintain the confidence of financial statement users.”

Usually, a company will estimate bad debts based on past experience. However the allowance aging method suffers from two weaknesses. First, the estimate of bad debt is based on endogenous variables only. This may not be realistic, as exogenous variables, such as unemployment rates, could reasonably be expected to have an effect on amounts collected. Secondly, the estimates are ultimately a result of judgment and therefore vulnerable to earnings management manipulation. Management can easily adjust both the bad debt rate applied to credit sales as well as the rates applied to an aging of receivables. In theory, a manager, wishing to manipulate earnings, could look at year-end financials and decide what number is needed in the bad debt expense account that would be most beneficial to the company as a whole and proceed with an estimation process which would provide the desired number.

2.3.3 Cluster Analysis and Regression Analysis

Fanning and Cogger's (1998) study uses an ANN to develop a model for detecting management fraud. The study is an examination of important publicly available predictors of fraudulent financial statements. The study finds an ANN model with a high probability of detecting fraudulent financial statements. This study reinforces the validity and efficiency of ANN as a research tool. The first step of Fanning and Cogger's (1998) study was to perform univariate tests to determine the statistical significance of different audit related variables. They initially started with 62 variables and 204 sample firms. However, the problem with univariate tests is that it was hard to determine if the association with the outcome was direct or whether there were joint correlations with a third variable. Also, univariate tests do not determine interaction effects. Consequently, logistic regression, linear regression, and quadratic discriminate analysis were chosen to compare with the ANN results. The findings show that the ANN produced results which were 63 percent accurate, while none of the other models produced results greater than 50 percent accuracy.

Contemporary statistical software packages make it tempting to build a credit model and assessing the provision for bad debts simply by analyzing past results using regression analysis. However, according to Coakley and Brown (1999), the major difference between ANN results and a statistically-based multiple regression approach is the process in which weights are assigned to the variables. ANNs are not static, but keep integrating new variables. Unlike the static regression model, where the equation is established and relied upon, an ANN interactively adjusts weights until the error is minimized. An ANN maps independent variables to nodes.

Each independent variable is given a weight within a node and the node itself is given an overall weight. Nodes are grouped into neurons. These neurons are then used to make an overall prediction. As the ANN predictions are compared to reported data (to determine accuracy), the ANN adjusts the individual neurons to provide better predictions in the future.

The research study of Feroz, et al. (2000) also provided some indication that ANNs are superior to logistic regression as well. Their study focused on firms targeted for Securities and Exchange Commission (SEC) investigations in order to predict the likelihood of an SEC investigation. Two analytical models were developed. One was a logistic regression model and the other was an ANN. In comparing the effectiveness of the two models, the logistic regression model had an accuracy rate of 52 percent while the accuracy of the prediction of the ANN model was 70 percent. The key difference between the two methods is that logistic regression output is based on training which is predefined, while ANN training is constantly evolving.

According to Quek, et al. (2009, p.166), "the neural network approach offers a more general model in bankruptcy prediction problems." The ANN approach does not assume any probability distribution or equal dispersion for its data. The authors acknowledge that while ANNs provide more accurate results than traditional statistical models, it offers little rational explanatory capabilities. According to Quek, et al. (2009, p. 166), the reason for the lack of explanatory power is due to the fact "it is difficult to relate the trained linked weights of a neural network into a language that is comprehensible to the human being." Quek, et al. (2009, p. 166) proposed a fuzzy ANN approach, where fuzzy ANNs are "universal data-mining tools" which "possess a strong capability to derive the intrinsic relationship between the selected inputs and outputs."

West (2000) compared the accuracy of ANN architectures against linear discriminant analysis and logistic regression (parametric models), *k* nearest neighbor and kernel density (non-parametric models), and classification trees. While the results of that study indicated logistic regression was the most accurate method, it also stated the results might differ if some of the ANN architectures were combined rather than assessed individually. According to West (2000, p. 1133) some feel “the advantage of the neural network scoring system is the improved function-fitting capability due to the intrinsic non-linear pattern recognition capability of the neural network.” Even the smallest of improvements, can translate into significant amounts of savings. At the time of West (2000) study, multi-layer perception (MLP) was the predominant method of designing ANNs. The design uses layers to group similar explanatory variables into larger independent variables. However, a mixture of expert approaches (which combines the power of numerous models) is more accurate according to West (2000) because this particular ANN was more accurate than any other model in the study. This approach would incorporate systems that have previously demonstrated predictive ability.

Falavigna (2008) conducted a survey of techniques used for default risk analysis. The goal of this study is to understand if it is possible to use complex systems for the analysis of default risk and which model is the best. The findings of the research indicate that default risk is more often accurately predicted by ANNs.

It has been demonstrated by prior research that ANNs can, in many instances, provide superior information than the information provided by traditional methods. These studies include Cadden (1991) which compared ANN predictions to multiple discriminant analysis results, Coats and Fant (1992) study uses a back-propagation method versus ANN, and Zhang, et al. (1999) study examines logistic regression versus ANN.

Altman (1968) was one of the first to address the issue of corporate bankruptcy. While acknowledging the importance of individual financial ratios, Altman (1968) warned against univariate analysis. He used the following example: a company could have low profits and solvency issues, yet have excellent liquidity. The last ratio tends to mitigate the first two ratios and could lead one to reaching the wrong conclusions. As a result, Altman (1968) indicated that an overall bankruptcy assessment should be based upon a combination of measures. This led him, after careful consideration, to suggest multiple discriminate analyses as the solution. He saw the major advantage of this method as having "the potential of analyzing the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics." In other words, rather than looking at financial ratios individually, certain combinations of ratios could be analyzed as a whole.

Using multiple discriminant analysis, Altman (1968) was able to obtain a relevant amount of accuracy in bankruptcy prediction. His final model used the following independent variables: working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value equity/book value of total assets, and sales/total assets.

CHAPTER III

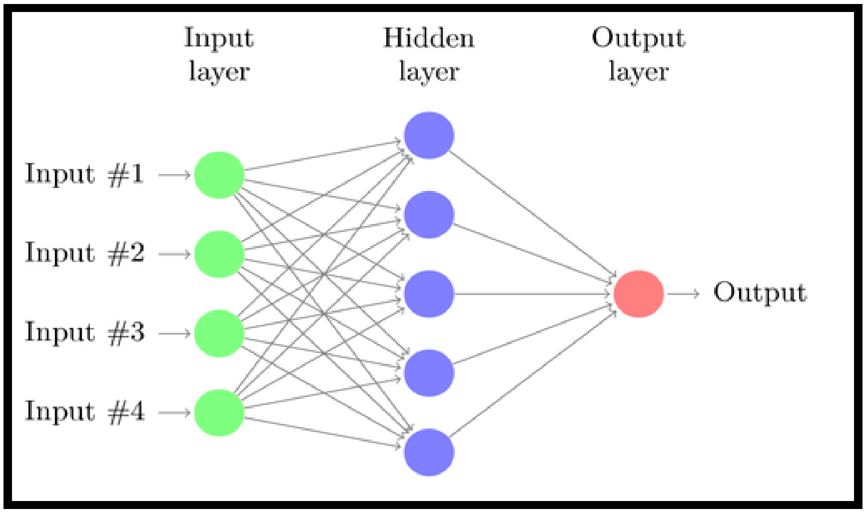
Neural Network Approach

3.1 Adaptive Learning Algorithms

ANNs attempt to simulate the human brain. A major difference between an ANN and the human brain is a human brain learns on its own and is unique to an individual. In contrast, an ANN must originate, at least in its early stages, from a set of predefined relationships. Both the human brain and the ANN will learn to recognize patterns and discover relationships in data. These patterns and relationships take the form of neurons and a group of neurons produces an overall result. If predicted results do not approximate actual results, the neurons must be adjusted. The major advantage an ANN holds over the human brain is that an ANN is capable of analyzing and recognizing patterns in large sets of data. The enormity of such large sets of data would overwhelm a human brain.

The diagram below depicts the inner-workings of an ANN system. The inputs represent independent variables and the hidden layer represents the neurons. The output layer represents the dependent variable, which in the current study is the allowance for bad debt.

Artificial Neural Network (ANN) Diagram



Author: Kjell Magne Fauske

The ANN method used by Aragones, et al. (2007) is back-propagation (see *Exhibit I*). Different variables were represented by hidden layers. The term 'hidden' indicates that single independent variables are actually derived from multiple and similar independent variables into a larger grouping. For example, suppose you had 200 independent variables. The back-propagation network may derive five categories (each consisting of 40 variables). These categories which are not visible during the back-propagation process actually represent single independent variables. As a result, instead of considering the impact of 200 separate variables, the process is simplified by considering only five independent variables (which are in actuality similar variables grouped together). According to Aragones, et al. (2007) a general rule of thumb is that no layer should have more than five elements. If more were introduced, it would make it harder for the ANN to generalize.

According to Ding, et al. (2011) a back-propagation network is good at unsupervised learning, adapting, and generalizing data. As stated above, a back-propagation network takes variables and places them into a larger grouping. These groupings, taken together provide an estimated total. Consequently, learning occurs in subsequent periods (as predicted outcomes are compared with actual outcomes). This type of network is based on an algorithmic system which is capable of adusting weights. Each grouping should approximate or generalize a particular facit. Thus a grouping which generalizes expense would consist of expense items.

3.2 Design Science

Information systems can be classified into two paradigms. In their seminal article, Hevner, et al. (2004), outlined the differences between these two paradigms. The first information systems paradigm is behavioral based. It addresses theories that attempt to explain human or organizational behavior. The second paradigm is a design science approach. The design science approach is not focused on behavioral theories, but instead, is focused on improving and aiding human and organizational capacity through the invention of novel and innovative 'artifacts.' An 'artifact' can be a computer-based solution which, according to Hevner, et al. (2004, p. 76), improves the "experience, creativity, intuition, and problem solving capabilities" of the user.

The design-science paradigm applies to this study in the following manner. First, this study qualifies does not seek to explain any sort of human or organizational behavior. Instead, it will use raw numbers to draw conclusions about the reasonableness of a company's bad debt estimates. The development of the artifact will address the nature of the problem and by extension describe the knowledge necessary to address the problem. This includes variable selection and data collection. The solution to the problem will include data preprocessing, testing, and evaluation. The result will be an ANN artifact capable of predicting a company's bad debts, and by extension, the reasonableness of its allowance for bad debt. Finally, as will be discussed later in the study, there are methods for determining the accuracy of the ANN output.

This study follows the design science paradigm. According to Hevner, et al. (2004), the design science paradigm requires the following: 1) knowledge and understanding of a problem domain, 2) a solution of the problem domain and 3) the design artifact which will accomplish the solution and 4) an evaluation of the artifact.

CHAPTER IV

Research Methodology

4.1 Research Questions

The research questions addressed by this study are: Can Artificial Neural Networks (ANN) be used to:

A) Categorize companies into groups based on the behavior of their bad debt expense and related allowance for bad debt using numerous ratios and financial statement data?

B) Derive accurate estimates regarding bad debt expense and the related allowance for bad debt using numerous ratios and financial statement data?

The uniqueness of this study should be noted. The study addresses data analysis from both an internal and an external perspective.

The ability to quickly categorize companies on the basis of their bad debt account would be helpful to financial analysts, independent auditors, and potential investors as it would allow them to arrive at preliminary estimates about the true nature of a company without performing detailed analysis. The categorization of companies into groups according to the behavior of their bad debt expense account would be beneficial to an external user(s).

The first goal of this study is to develop an ANN capable of providing a quick means for determining important characteristics about a company's bad debt expense, given a set of independent variables. It provides a quick snapshot of the company, which in turn would influence initial assessments in regards to a company's potential strengths and/or weaknesses. External users have access to publicly available financial statements, but they would not have inside access to a company's detailed accounting system. Limited access to data makes specific predictions problematic at best. In addition external users are more interested in basic evaluation, such as classifying a company into a particular group based on the behavior of its bad debt expense account. They would not be as interested in specific numerical predictions of the bad debt expense account at year end. It would be unlikely such individuals would want or need to spend vast amounts of time on individual companies.

An internal user would have less use for categorizations. Unless attempting to benchmark performance against a company of similar size and product offering, a system which merely groups companies into categories would have virtually no use. In some cases, it may be beneficial to see how the ANN classifies a competitor, but the classification is just an estimate. The main focus in this situation would be self-evaluation. Only in very rare cases is a company going to reveal intricate details about its accounts receivable to outside sources. Whereas attempts to make specific predictions by external users is hampered due to the fact they would not have unrestricted access to all relevant data, no such handicap exists for an internal user, who has unrestricted access to all relevant data.

In contrast, if a company applies an ANN internally, it would have detailed information regarding its own accounts receivable. As a result, it could proceed with the type of analysis addressed by the second goal of this study, which is prediction. An ANN capable of producing actual numerical predictions for future years would be much more valuable to a company than one capable of classification only. This study applies the same independent variables to each company in an effort to make predictions. However, it is unlikely that any two companies would actually be influenced by the same identical firm and macro variables. Each company is unique and only internal users are capable of fully understanding which variables are most relevant to them. In addition, an internal user would be better able to add and subtract independent variables in an effort to improve ANN prediction accuracy.

4.2 Development of the Artifact

The first phase of ANN development is unsupervised, meaning there are only input variables but no output variable. Using this input data the ANN begins to classify the data. The second phase of the process is to present a new set of data to the ANN along with output data (i.e., supervised learning). This allows the ANN to adapt as it learns to assign weights to the original input variables. These weights relate to the relative predictive power of each input variable in explaining the output data. Over time, an ANN begins to 'learn' by adjusting the weights attached to input variables and/or adding new variables. This characteristic is often referred to as back-propagation. This is the main advantage of an ANN, its adaptability. It can adjust its node weights through usage of a learning algorithm. ANNs can act as pattern recognizers and predictors. ANN 'learning' occurs when an original set of variables is introduced into an ANN model and compared with actual book value results. Over-fitting is reduced by back-propagation. The ANN training patterns are referred to neurons (items that process information) which learn by adjusting weights assigned to different variables (back-propagation) as more output data is gathered. Over time, the ANN should continually make adjustments so that the difference between predicted ANN values and actual accounting book values should be very small.

This study employs the usage of back-propagation through the usage of two ANNs. Each of which will be used to accomplish the objectives listed above. The two main functions that these ANNs will perform are classification and prediction respectively. The classification portion will be used to classify companies into different groups based on their allowance for bad debt fluctuations as too low, reasonable, and too high. The prediction portion will make actual numerical predictions of the allowance for bad debt accounts on a company by company basis.

The artifact proposed by this study could be based on any number of variables. There are many external factors such as societal resources and institutions, competitors, and consumers that play a role in a company's success or failure. Consequently, this study will attempt to identify relevant internal and external variables to use in the development of the artifact.

4.3 Dependent Variable: Allowance for Bad debt – Year End

The Allowance for Bad debt provides an ideal method for testing ANNs because one can examine this balance and analyze its changes over time. As a result, predictions provided by an ANN method can be compared against traditional statistical methods of predictions such as regression. Further, for classification purposes, the bad debt account can be analyzed in simple terms (i.e., too high, accurate, or too low).

This study focuses on amounts of bad debt a company reports to the public. Items such as beginning and ending allowances for bad debt were obtained through the Wharton Research Database Services (*WRDS)* system. Unfortunately, the exact details regarding changes to allowances for bad debt were not provided through *WRDS*. Companies typically lump the pertinent amounts into a broad category called general and administrative expenses. Thus, the allowance for bad debt was obtained through the SEC's *Edgar* system. The allowance for bad debt changes from year to year due to the following events: 1) Additional accounts are estimated to be uncollectible and 2) Some accounts are actually written off.

Riley and Pasewark (2009) detailed 3 methods for assessing the accuracy of the Allowance for Bad Debts Account:

1) Compare Bad Debt Expense with Actual Write Offs. Keeping in mind that bad debt expense and the related allowance for bad debt are essentially educated guesses, however one can determine the accuracy of these amounts by examining actual

results. Ideally the bad debt expense should match closely with actual write-offs. Consequently, over time, the bad debt expense to write-off ratio should be close to one. If the number is less than one, it means a company may be underestimating its bad debts. If the number is greater than one, it may mean a company is overestimating bad debts.

2) Compare Beginning Allowance for Bad debt to Actual Write-Offs. If write-offs exceed the beginning balance in the allowance for bad debt, it could be concluded that the allowance was not sufficient to cover bad debts. The implication is that the net accounts receivable are overstated. Likewise, if bad debts fall far short of the allowance, it may indicate a company's allowance account is excessive. In order to test the accuracy of the allowance for bad debt, several years of data need to be examined with regards to the mean and standard deviation of the ratio of allowance for bad debt to actual write-off. A high standard deviation would imply greater volatility, which in turn would denote a situation where a company may operate at extremes. In other words, rather than producing amounts that are relatively constant, a company with a lot of volatility may produce a number that is unusually high or low.

3) Assess the Allowance Exhaustion Rate. This is a fairly straightforward process. The beginning allowance amount is compared to the actual bad debt write-offs. If a company has a $2,000,000 balance in its beginning allowance for bad debt and actual write-offs are $1,800,000 during the year and $200,000 in January of the subsequent year, then the exhaustion rate is 1 year 1 month. Ideally, the number should be close to one.

4.4 Independent Variables

A set of sixty independent variables was chosen for this study. The reason for the large number of variables is consistent with the major aim of this study, which is to provide better estimates of bad debt using both endogenous and exogenous variables. The traditional methods of estimating bad debt are subjective. If an income statement approach is used, then one has to estimate the percentage of credit sales which will ultimately prove uncollectible. If a balance sheet approach is taken, one has to estimate the percentage of ending receivables balance which should prove uncollectible and/or make such an estimate based on an aging of accounts schedule. In actuality, the allowance for bad debt may be heavily influenced by any number of factors, both internal and external. In some cases, only a few variables may be sufficient to estimate a company's ending bad debt allowance, whereas in other cases, a relatively large number of variables may be needed in order to determine an accurate prediction and/or classification

The independent variables in this study were grouped into three categories. The first two categories pertain to firm specific variables: one category is calculated firm specific ratios and the second category consists of values taken directly from the financial statements. The third category of independent variables consists of macroeconomic measures external to the firm. The independent variables and their justification for inclusion in the model are listed below.

Ratios provide information about a firm that may not be readily apparent on a firm's financial statements. Ratios are used to assess different aspects of a company's performance and how effectively (or ineffectively) the company may be performing. The usage of ratios enables one to compare companies of differing sizes. However, the most important characteristic of ratios is they help enhance the quality of the financial statements.

4.4.1 Liquidity Ratios

Liquidity ratios gauge how well a firm is able to generate cash. GAAP mandates the use of accrual-based accounting, however, such a method does not necessarily address the need for immediate capital.

1) Current Ratio – If a company does not have sufficient cash balance, it may be tempted to understate the allowance for bad debt accounts in order to appear more solvent.
2) Acid Test/ Quick Ratio – As with the current ratio, the temptation may be to manipulate net receivables in order to appear more 'healthy' financially.
3) Ratio of Cash to Current Liabilities – If a company is suffering major cash flow problems, the temptation would be to overstate net receivables by understating the Allowance for Bad Debt.
4) Days Sales in Accounts Receivable – If this number begins to trend upwards, it should impact the allowance for bad debt accounts because it implies that it is taking longer to collect receivables, which increase the chance for defaults.

4.4.2 Efficiency Ratios

These ratios indicate how well the company utilizes its assets.

1) Accounts Receivable Turnover – This is mainly a measure of volume because it indicates how often the average receivables of the business issued and collected during the year. This can be associated with the allowance for bad debt because the higher the volume of credit sales, the greater the probability that some accounts will default. This measure also is an indicator of how quickly a company collects its receivables. From an aging of accounts' approach, the longer it takes to collect receivables, the greater the likelihood of defaults.

2) Inventory Turnover - Indicates how many times the average inventory of a business is purchased and sold. The higher the volume of credit sales the greater the probability the accounts will default.
3) Days to Sell Inventory - Indicates, how long it takes to sell inventory. This has an impact on credit sales, which in turn should have an impact on the allowance for bad debt accounts. If it takes too long to sell inventory, it may be because its credit policies are too strict or their competitors are selling the same items at lower prices. If in fact the problem is overly strict credit policies, the level of defaults should be low, which would make the allowance for bad debts low. If inventory is sold quickly (because credit policies are too lenient as opposed to selling at cheaper prices than competitors), this may lead to a high level of defaults and a high allowance for bad debts.

Relation of Liquidity and Efficiency Ratios to Allowance for Bad Debt: The first four ratios, which measure, with varying degrees, the ability of a company to pay its debt can have a significant impact on the allowance for bad debt accounts. If these ratios are habitually low for a company, it may indicate that there is a cash flow problem. The accounts receivable turnover ratio indicates how long it takes to collect credit sales. If the profit margin on credit sales is high, this number doesn't necessarily have to be large, but if it is small and the profit margin is also small, this could indicate a problem. Since that the aging of accounts receivable is acceptable for GAAP purposes, this measure seems appropriate for inclusion. The inventory turnover and days to sell inventory can be logically associated with credit and by extension the allowance for bad debt accounts. If pricing is not an issue (i.e. a company's prices are roughly equal to its competitors), inventory turnover combined with a relatively large number derived from days to sell inventory, may indicate a strict credit policy. If the opposite holds, it may indicate that the credit policy is too lenient (once again, assuming pricing is not the issue). Lastly, the days sales in accounts receivable indicates how vigilant a firm is about collecting receivables. It also indicates whether it is granting credit to individuals who have the ability to pay on their accounts as they become due.

4.4.3 Profitability Ratios

Profitability ratios are primarily used to assess management performance. Investors are interested in seeing maximum returns on their investment. In simple terms imagine that an investor is faced with two choices; 1) they could invest their money in a low-risk investment, or 2) they could invest in a more risky investment, but one that pays higher interest. Since interest is a factor of risk, a safe investment will pay less interest than a riskier investment. The same principles apply to profitability. Those who invest in the stock of a company want to see a return commensurate with risk. Since the allowance for bad debt accounts contains a subjective component (even if GAAP is followed), management may be tempted to manipulate the allowance for bad debt account in order to meet earnings projections and expectations. Additionally, from the viewpoint of creditors, profitability ratios are an indication of the health of a company and can influence whether or not they grant credit.

1) Ratio of Income to Sales - Proportion of sales dollars that contribute to gross profit. This ratio has several implications for the Allowance for Bad Debt Account. First, credit sales are recorded as credit even if the customer fails to pay the associated account. Gross profit is netted against bad debt expense and other expenses to derive net income. Frequently, Bad Debt expense is included as part of general and administrative expenses and is not included as a separate value on the income statement. Consequently, if

defaults are high, actual write-offs could be ‘concealed’ by simply placing it in a broader category of expenses. Second, the Allowance for Bad Debt account could simply be manipulated at the end of the year in order to derive a particular value for net income.

2) Ratio Sales to Average Total Assets - Measures whether an adequate return is being earned on average total assets used by the firm. When Bad Debt Expense is recorded, it is treated as just another expense. When a company determines that an account is in fact uncollectible, it is recorded as a direct reduction of accounts receivable. Thus, a company can manipulate this ratio through credit policies. In order to achieve a particular return, a company could temporarily implement relatively lenient policies, even if it is for just a short period, in order to inflate sales. Hence, the allowance for bad debt will be impacted.
3) Ratio of Cost of Goods Sold to Sales – Proportion of sales dollars that relate to inventory costs. From a managerial accounting viewpoint, once a company reaches a break-even point, it has more options available to it in terms of credit policies. If the majority of inventoriable costs have already been re-captured through sales, the company may revise credit policies accordingly as the danger of producing a Net Loss has greatly decreased. By extension, the Allowance for Bad Debt is affected whenever credit policies are changed.
4) Ratio of Depreciation and Amortizations to Sales – A business which has a large investment in fixed assets and equipment (depreciable assets) has a higher break-even point than a company with a comparatively small investment in such assets. Consequently, this ratio impacts sales goals, which ultimately impacts the Allowance for Bad Debts.

5) Return on Total Assets – Provides an indication of the investment required to earn each sales dollar. If a company emphasizes the investment associated with the generation of each sales dollar, then the company will not want make credit sales to customers who will ultimately not pay because the sales represent a waste of investment capital. As a result this ratio should impact credit policies and eventually the allowance for bad debt.

6) Return on Common Equity – Owners have expectations in regards to their investment returns. As a result, management needs to accurately evaluate and establish a healthy balance between the credit policies that generate additional sales dollars and the monetary lost due to defaults. Hence, management must keep a watchful eye on the balance in the Allowance for Bad Debt.

7) Earnings Per Share (EPS) Diluted Excluding Extraordinary Items (EI) and Discontinued Operations (DO). There are several reasons to believe that each of the above EPS items would impact the allowance for bad debt. First, when a segment is disposed, any accounts receivable and their associated allowance for bad debt is eliminated from the overall company records. Therefore, a company which presents consolidated financial statements could potentially show a large difference between beginning and ending allowance for bad debt due to the entire segment of the business and its bad debt has been eliminated. Second, if a company decides to dispose of a segment, it could entail a very large write-off of accounts receivable. Such an expense is frequently difficult to determine and can be included with other expenses associated with a discontinued segment. Since EPS is such an important measure, management may have an incentive to use earnings management techniques to make this number appear favorable.

8) Ratio of Income on Assets to Sales – This is a measure of net profit, expressed as a

percentage of sales. It shows how much of each sales dollar results in net profit. Management can very easily manipulate this amount by under or overestimating the amount that should be reflected in the ending allowance for bad debt.

9) Ratio of Research and Development Costs to Sales – This ratio expresses the percentage of current sales which are re-invested in the business for purposes of developing new products. One would expect a company with relatively high R&D expenses to have more stringent credit policies due to the need for immediate cash than those companies with relatively low R&D expenses. Hence, the makeup of the credit polices as influenced by R&D will impact the allowance for bad debt.

10) Ratio of Income Taxes to Sales – A measure of income tax in terms of a constant rate which is applied to sales. One can reasonably expect management to find a mixture of credit policy and bad debt expense which maximize net cash flow (i.e., the extra cash generated by offering items on credit should exceed both the amounts that prove uncollectible as well as the amount of corporate income tax that must be paid).

11) Ratio of Price to Common Dividends – This ratio measures cash flow per common share of stock (i.e., dividends). The allowance for bad debt is a factor which must be considered because a high allowance for bad debt could negatively impact stock price. However, credit policies which produce a large number in the allowance for bad debt account, could increase cash flow and ultimately make higher dividends possible.

12) Ratio of Price to Earnings Primary – Also known as the P/E Ratio. Measures how much investors are paying for each unit of net income. A component of overall earnings is bad debt expense, which is related to the allowance for bad debt.

13) Ratio of Price to Sales Primary – Similar to P/E Ratio, but the focus is on sales instead of

net income. As long as credit policies are not too inappropriate, this ratio can be improved by methods which impact the ending allowance for bad debt.

14) Common Stock Return Fiscal Year – This ratio measures the return on owner investment. Return on owner investment includes revenues (sales) and expenses (such as bad debt expense) which impact allowance for bad debt.

Relation of Profitability Ratios to Allowance for Bad Debt: These ratios address several management and owners expectations which impact allowance for bad debt. For instant, management is expected to earn maximum returns and investors expect and demand management to make decisions that will result in attractive returns. Ultimately management is often evaluated on such measures and quite frequently their bonuses are tied to the end results. Since the allowance for bad debt account is a subjective measure combined with the fact that net income is measured on an accrual basis, there may exist a temptation for management to manipulate the allowance for bad debt account to meet expectations and realize compensation bonuses and incentives. Assuming the reported amount of allowance for bad debt is accurate, it most certainly can be affected by cash flow expectations. In order to meet such expectations management may be tempted to lower credit-granting standards in order to generate cash. If the credit-granting policy is reasonable, but not necessarily wise, lowering credit standards could result in more cash collections in the near term, but ultimately lead to higher default rates in the long term.

4.4.4 Solvency Ratios

Solvency ratios are indicators of a company's ability to meet its debt obligations. If a company finds itself with inadequate cash to pay current debt, its ability to continue into the future becomes a serious concern. Creditors have the option to impose penalties on the company and/or force it into bankruptcy. The decision of a lender to grant a company credit includes an evaluation of the company's allowance for bad debt.

1) Ratio of Total Debt to Total Assets – If this ratio is close to 1, it indicates the company is highly leveraged. In such cases, the company's debt may be almost as much, if not more, than its assets. If a company does not adequately account for bad debts, the number provided to creditors may not be accurate. Thus, in order to gain credit, a company may be tempted to understate their allowance for bad debt.

2) Ratio of Cash Flow Assets Pre-Tax to Interest – This is the operating cash flow of a company (earnings before interest and taxes) divided by interest. It indicates whether a company's actual cash flow is sufficient to pay interest. Companies typically have the option to factor receivables. In some cases (factoring with recourse) all the risk resides with the company factoring its receivables, as the factor will demand payment for accounts it cannot collect. Interest is not something negotiable in most cases. It is a set amount agreed upon at the time a loan is obtained. If a company fails to pay its debt obligations, a creditor can take legal action. As a result, in order to make receivables appear more attractive to a factor, a company may manipulate net receivables through the Allowance for Bad Debt account.

3) Ratio of Market Value Equity to Book Value Equity - If this ratio is 1, it indicates the market values the company's stock the same as the company values its own stock. If this value is less than one, it means the stock could be undervalued. This undervaluing may simply be a reflection of timing differences, which means the market price will eventually adjust to reflect book value. Likewise, undervalued stock may indicate the market sees

potential problems with the company which are not readily apparent from the company's financial statements.

4) Ratio of Total Assets to Shareholder's Equity- This measure is also referred to as the equity multiplier. Companies have two options when it comes to raising capital. They can either issue stock or they can borrow money. A high total asset to shareholder's equity ratio indicates the company is relying more on debt to finance operations than on owner investments (i.e., stocks). As a company becomes more leveraged with debt, there exists an incentive to manipulate the allowance for bad debt accounts in an effort to meet debt obligations.
5) Ratio of Interest Expense to Sales – This ratio indicates the degree to which current sales exceed borrowing costs. However, credit sales do not necessarily represent cash inflow. Credit policies can be changed to increase sales and this would have a direct effect on bad debt.
6) Ratio of Price to Operating Cash Flow Primary – This is similar to the P/E Ratio, but the focus is on actual cash realized, not accrual based net income. Hence, this ratio measures how the company share price is influenced by actual cash flows. This is a useful measure, because under accrual-based accounting, there are a myriad of ways, including the manipulation of the allowance for bad debt, to improve net income.

Relation of Solvency Ratios to Allowance for Bad Debt: The Solvency Ratios involve cash flow issues. These ratios cover numerous issues facing a company. They address questions ranging from whether a company can meet its debt obligations to how its actual cash flow affects stock price. If the solvency ratios indicate financial problems, the temptation may be to lower credit standards in order to generate immediate cash if a company is faced with an inability to meet its cash obligations. Under such a scenario, if more credit accounts are allowed, it will result in increased cash collections in the short term. Also, the new accounts can always be factored to generate quick cash. Regardless of which situation a company employs, the Allowance for Bad debt will be affected.

4.5 Variables from Company Financial Statements

Most of these variables can be found on the income statement or balance sheet, while a few can be found in the notes to the financials. A few key variables associated with the allowance for bad debt accounts were taken from the financial statements: advertising expense, common stock return fiscal year, cost of goods sold, dividends cash common, dividends cash preferred, number of employees, interest expense, total inventories, net income (loss), operating activities net cash flow, operating cash flow, receivables estimated doubtful- prior year, total net receivables, research and development expense, retained earnings net other, and net sales.

These financial statement variables reflect the results of operations and company decision-making. In regards to Balance Sheet and Income Statement Items, variables such as net receivables, total inventory, cost of goods sold and sales all have a direct impact on the allowance for bad debt accounts. Miscellaneous items, which include variables such as number of employees, stock prices, dividends paid and cash flows may not directly impact the allowance for bad debt accounts, but they do reflect the overall health of a company and as such must be considered when calculating the allowance for bad debt Accounts.

4.6 Macroeconomic Variables

1) Bank Credit at All Commercial Banks – Indicates the degree to which companies can borrow funds. A company will manipulate the allowance for bad debt if doing so

would increase the likelihood of securing a loan.

2) Civilian Unemployment– If people are not working, their ability to repay debt is impaired. If 100% of all accounts receivable were collected, it would indicate an overly strict credit policy. Credit policies are often the product of careful consideration. Unfortunately, a person who has the means to repay debt today may not have the means to repay debt tomorrow due to an unexpected job loss. Clearly, this would impact the allowance for bad debt.

3) Consumer Bankruptcy Filings – Consumer debt is often discharged in bankruptcy (i.e., becomes a bad debt and is permanently uncollectible). As the number of bankruptcies increases, the potential for accounts defaulting increases. The higher the number of defaults, the higher the number of accounts a company will have to write-off.

4) Consumer Credit Outstanding (in Millions) – As this number increases, the greater the likelihood of defaults as individuals may have been granted more credit than they are capable of paying. This variable can also be an indicator, that a majority of the companies are leaning more towards more lenient credit policies. A large amount of consumer debt outstanding increases the likelihood that a company may grant credit to a customer without fully realizing the total amount of debt the customer owes to different sources. Failure to ascertain customer debt information will impact the allowance for bad debt as defaults begin to materialize.

5) Consumer Price Index (All Items Annual Average) – Measures the cost of living. It addresses the prices of basic necessities. The larger this number, the lower the amount of disposable income one has to pay existing consumer debts. If a person is faced with the bleak prospect of buying food or paying rent or mortgage, they are most certainly going

to opt for the most essential items. Companies that sell non-essential products, such as entertainment devices, would be impacted because a consumer faced with limited income, is going to take care of essentials needs first. Therefore, sellers of non-essential goods may experience higher default rates.

6) Corporate Bond Yield – This is a measure of how much it costs a company to borrow money. The higher the cost of borrowing, the greater the incentive to manipulate the allowance for bad debt to make net receivables more appealing.

7) Disposable Personal Income– A large number indicates that consumers have more money available to repay debt and buy non-essential/discretionary items. This variable not only serves as an estimate of the amount of debt that will be repaid, but also the amount of new credit purchases.

8) Dow Jones Industrial Average – This is a measure of investor confidence in the capital market. The Sarbanes Oxley Act of 2002 was the Federal government's response to egregious accounting policies; policies which included fraudulent amounts in the allowance for bad debt. Low investor confidence could be interpreted to mean greater scrutiny of company financials. Therefore, earnings management techniques involving accounts such as the allowance for bad debt would be more difficult to accomplish without investor skepticism.

9) Manufacturers' Shipments and Inventories – Indicates the amount of goods available to consumers, which impacts credit granting. Merchandising companies can only create a finite amount of new credit accounts, and this is heavily impacted by the amount of inventory they have available to sell.

10) Personal Consumption Expenditures – If the population is spending, then companies will

sell more of their products and services. This would mean larger accounts receivable and greater complexity regarding the allowance for bad debt.

11) Personal Savings – First, if people are saving, then there is less likelihood that new accounts receivable (and their associated risks) will be issued. Second, if individuals have savings in reserve, it increases the likelihood they will have sufficient funds to pay their debts as they become due.

12) Stock Price at the End of the Calendar Year –Management bonuses and compensation are often tied to items such as stock price. If a company's stock has risen in market price since the beginning of the year, management will be rewarded. However, such incentives do increase the temptation to employ earnings management techniques (which includes the allowance for bad debt) in order to achieve desired results.

13) Real Gross Domestic Product– Indicates the output of an economy, adjusted for inflation and/or deflation. It is rare to see deflation occur in the United States economy. The trend has almost always been towards inflation. The implication for the allowance for bad debts is clear: A person making a set salary, may suddenly find that their income is no longer sufficient to pay all their debts.

14) Unemployment Level Looking for Full Time - This is a potential indicator of consumers who have debt, but do not have income at present. Unemployment negatively impacts accounts receivable. A factor that should be implicit in determining the allowance for bad debt should be unemployment rates. People cannot repay debts if they have no income.

15) Unemployment Level for Persons 25-54 Years Old– This indicates the unemployment level amongst consumers most likely to incur debt. These individuals are not on fixed

income and are inclined to purchase non-essential items such as cars, electronics, and other goods. If unemployment among this group is high, it can have dire consequences regarding the likelihood a company will receive money owed from these persons.

<u>Relation of Macroeconomic Variables to Allowance for Bad Debt Account</u>: These variables consist of items that reflect the larger business environment as a whole, not just a specific company. One of the major contributions to increasing the accuracy of the allowance for bad debt using ANNs is the use of wider economic variables. Companies typically examine their own history and their own past experience when determining the amount reflected in the allowance for bad debt accounts.

Ignoring exogenous variables can have significant consequences. For example, a company may have always enjoyed low default rates on accounts receivable. Perhaps they have excellent methods for determining whom to grant credit. The company could hypothetically see little to no difference in default rates over the years. In addition, the company may remain static and conduct business as usual. However, there are circumstances beyond the control of such a company. If the overall economic environment in which the company operates changes, it is quite likely their default rates will increase. For example, if the unemployment level increases and personal disposal income decreases, it means there may be customers who are unable to pay what they owe.

The economy specific variables chosen for this study by no means encapsulate all the factors which can be used to measure a company's operating environment. These variables represent a small sample of factors which one could logically associate with default rates and by extension, the allowance for bad debt.

CHAPTER V

Creation of the Artifact

5.1 Data Collection

Most of the accounting financial research data were extracted from the Wharton Research Database Services (WRDS) system. The main source of exogenous variables was the 2010 *Economic Report of the President*.

The initial aim of the study was to examine two sets of data populations based on their Standard Industrial Classification Code. One was to be the retail category (5200-5990) and the other was to be the commercial banks/saving institutions category (6020-6036). Company data were retrieved from the WRDS database using SIC codes. However, it should be noted that useful information (for purposes of this study) were only derived for retail category companies. As a result, the entire sample consists of companies in the retail category. In order to be included, a company had to have data covering every year from 1998 through 2009 (12 years).

Data Sample Selection Process:

Commercial Banks/Savings Institutions	162
Retail Businesses	350
Total Companies in the Original Sample	512
Unusable Commercial Banks/Savings Institutions Observations	(162)
Unusable Retail Businesses Samples	(264)
Total Usable Samples	86

After analyzing the companies, a complete data set of 86 companies (all retail) was selected. These 86 companies were all in the retail sector. Retail companies are required to disclose an enormous amount of financial information. Additionally, theretail industry companies all use the same basis of accounting – FASB accrual basis of accounting. Whereas, the banking industry companies use Regulatory accounting; a different basis of accounting with limited disclosure.

Since the independent variable of this study was allowance for bad debt, it was crucial to obtain the variables which contributed to the change in the allowance for bad debt account each year. Simply taking the amount in the allowance for bad debt one year into the future and subtracting the current balance does not provide meaningful data. The entire difference cannot be attributed to bad debt expense. The ending balance in allowance for bad debt is a product of both the bad debt expense for the year as well as accounts receivable written off during that year.

Companies frequently group bad debt expense into the broader category of General and Administrative expenses on their Income Statements. The amounts for these accounts were frequently omitted in the WRDS data. Consequently the data was incomplete. Therefore, in order to obtain bad debt expense and write-offs for those companies missing such data, a search was made of the 10-K filings with the SEC through the EDGAR database. The 10-K filings included: *Schedule II – Valuation and Qualifying Accounts*. This schedule provides specific bad debt expense and write-off amounts. This information made *Schedule II* an invaluable source of information as it enabled analysis on actual amounts of bad debt expense recorded. Twelve years of data were collected. The first year, 1998 was used to begin the training process and consisted of 60 independent variables. In subsequent years, 68 independent variables were analyzed for each year. The real goal of the study was to analyze the years 1999-2009, (11 years or approximately one decade). The ANNs in this study were provided this amount of data in order for the 'learning' process to be demonstrated. Each of the 86 companies had 68 independent variables and one independent variable for each year from 1999-2009. This resulted in a total of 65,274 data values in total with each individual company having 759 data values.

5.2. Implementation of Neural Networks

Both Excel and SPSS were used to analyze the data. These programs were used to provide the measures against which the performance of the ANNs used in the study were compared. Both *NeuroXL Clusterizer* and *NeuroXL Predictor* are add-ins to Excel. These add-ons are not only appropriate for the present study, but they are also affordable for any company desiring to use them.

5.2.1 NeuroXL Clusterizer

This study uses two ANN programs. The first program is known as *NeuroXL Clusterizer (*see *Exhibit II and Exhibit III* screenshots). This program has the ability to determine the weights to assign to variables. Furthermore, this program can allow for the grouping of certain variables and how many such groups to create. As long as the variables are able to be obtained and put into spreadsheet form, this program should carry out the aforementioned task of classification by an external user.

In the actual study, 68 variables (see Table 2) were used to classify each company into a particular category. A portion of the data entered into the *NeuroXL Clusterizer* for this study can be seen in *Exhibit III*. Companies were grouped by color, which made it easy to assign a category value to each company.

NeuroXL Clusterizer allows for the user to decide how many clusters will be used. In this study, 3 clusters were specified. This resulted in 3 color codes (see *Exhibit II*). Based on the colors assigned, a category number was manually assigned to each company. The usage of 3 clusters was chosen in order to classify companies into those that recorded insufficient bad debt expense (category 1), those that recorded a proper amount of bad debt expense (category 2) and those that recorded too much bad debt expense (category 3).

NeuroXL Clusterizer uses the following methodology to group companies into categories: First, averages for the primary individual category of interest (bad debt expense) were calculated. This involved a comparison of the average of an individual company's bad debt expense to the average bad debt expense for all companies in the same category combined. Second, the averages of secondary categories, for a particular company are compared with the averages of each secondary category (in a fashion similar to that described above for bad debt expense). This is done to determine key characteristics (i.e. average values) on a category by category basis. Next, a weighted average calculation was used to determine "the relative importance of each secondary category average in regards to average bad debt expense." Lastly, cluster weights were calculated to indicate "the weight of each cluster, which represents the percentage of items belonging to the cluster." All of these steps resulted in each company being assigned a color based on its cluster membership.

The data collected in this study covered the years 1998 through 2009. The *NeuroXL Clusterizer* was only capable of analyzing 10 years of company data (due to the number companies and variables per company). It could not analyze the entire data set at once. However, given the magnitude of the data involved (10 years), with each year containing over 60 variables), a step-by-step process was used to emulate learning. In order to emulate learning, a progressive approach was used. Running the program one time on all the data would not demonstrate a learning process even if it had been possible. The *NeuroXL Clusterizer* was first given only 1998 data to analyze. Second, the companies were clustered based on 1998-1999 data, then 1998-2000 data, and finally 2000-2009 data. As the time periods changed, the categories into which some of the companies were assigned changed as well.

Once a full data set of companies and their respective clusters was calculated, the next step was to evaluate the performance of *NeuroXL Clusterizer*. Several evaluation methods were considered. One method of classification was based on visual observation the other method of classification was based on statistics. The visual method relied on conditional formatting using icons and bars. In both cases, the cluster in which *NeuroXL Clusterizer* placed a company was very close to the cluster assigned to a company using both evaluation methods.

On a year by year basis, calculating the bad debt expense to write-off ratio suggested by Riley and Pasewark (2009) proved extremely difficult. If a company had no write-offs, or did not record bad debt expense, the ratio would have a zero in it and therefore be meaningless. Hence, for the present study, the average bad debt expense, covering 1999-2008, was compared against a 'lagged' average write-off amount, covering 2000-2009. Consequently the average ratios for bad debt expense and write-offs (covering 1999-2009) were calculated.

Variability in the measurement of bad debts and the related doubtful accounts needed to be considered. In order to incorporate variability, the standard deviation of each company's average ratio of bad debt expense to lagged bad debt write-off was calculated. This amount was calculated using 10 observations (as outlined above). Given that bad debt expense is an estimate of a company's current year receivables expected to default, it is appropriate to measure the accuracy and reasonableness of that estimate against subsequent year write-offs. Thus, the standard deviation resulting from that ratio is a good indication of variability.

Each company's bad debt expense to lagged write-off ratio was computed over a period of ten years. Next, the average for each company's average bad expense to lagged write-off ratio was calculated along with the standard deviation. For each company, the standard deviation was added to and subtracted from the company's average bad debt expense to lagged write-off ratio to determine a range for each company. This provided a standardized normal distribution range for approximately 68% of the data.

The statistical method chosen to categorize companies into groups was the two-step clustering procedure in SPSS. This method was used to analyze every company and its respective variables. This method was more appropriate for a relatively large data set which possessed many continuous variables. It also allowed for the specification of the number of clusters.

The visual-based method created clusters visually for companies based on the ratio of average bad debt expense to average write-offs rather than using a computational algorithm such as that used by SPSS. Cluster categories using this method were derived through visual binning with conditional formatting icons and line bars in Excel. According to IBM SPSS (2011): "Visual Binning is designed to assist one in the process of creating new variables based on grouping contiguous values of existing variables into a limited number of distinct categories." Though Microsoft Excel was used instead of SPSS for this purpose, the process is the same. According to IBM the process is useful when tone must "collapse a large number of ordinal categories into a smaller set of categories." For this research a continuous variable (will be) is collapsed into three categories. The three categories match the number of categories for the SPSS clustering.

5.2.2 NeuroXL Predictor

The second ANN program used in this study is called *NeuroXL Predictor* (see *Exhibit IV* for screenshot). This study used 68 independent variables and 1 dependent variable (Bad Debt Expense) to derive numerical predictions of bad debt expense. *Exhibit IV* shows only a portion of the data that was actually used to derive numerical prediction of bad debt expense. The steps involved in *NeuroXL Predictor* to derive a numerical prediction for a company are as follows:

1) A set of learning variables for a company is specified which will also serve as predictor variables in regression. In this case, it would include 11 years of independent variables (68 variables per company per year). The eleven covered years were 1999-2008.
2) A learning set of dependent variables for a company is specified. In this case it would include the ten ending amounts for a company in the allowance for bad debt from 1999-2008. (Note, the dependent variable value for 2009 is not specified anywhere in the model).
3) After steps one and two, the ANN is now ready to make predictions for a company based on what it has learned. Thus, the prediction set of independent variables is specified: in this case it would include all 68 independent variables for a company for each of the past eleven years (1999-2009).
4) The last step is to provide a range or area of the spreadsheet where the actual prediction for 2009 is displayed. This number can be seen in *Exhibit IV*. It is highlighted in red.

The paramount objective of this research is to develop a model and use variables which have not previously been used in the estimation of the Allowance for Bad Debts Account. The main artifact in this study is the actual numerical predictions provided by *NeuroXL Predictor*. While *NeuroXL Clusterizer* is adequate for providing basic guidance and initial expectations based on classifications, *NeuroXL Predictor* is much more powerful in that it can provide specific predictions.

According to its developers, *NeuroXL Predictor's* ability "to discover non-linear relationships in input data makes it ideally suited for forecasting dynamic systems." *NeuroXL Predictor* operates as follows (see *Exhibit V*): First a minimum weight delta must be defined. This defines the amount by which the weight assigned to a variable changes with each learning iteration. In this study, the ANN was instructed to assign .01 as the minimum weight delta. Next, epochs had to be specified. According to the developer, an "epoch is a full cycle of neural network training on the entire training set." (per *Neuroxl.com* website). Next a minimum weight delta is defined. In this study, the epoch was assigned a value of 10,000, which means that the ANN ran 10,000 learning iterations on each variable. Given that this number was very high, in theory it should mean that the final weights assigned by the ANN are as close to accurate as possible. The learning rate defines the rate at which the network "learns." This, in turn, has an impact on when the ANN will derive predictions that start to closely align with actual results. Finally, momentum impacts the rate and degree to which the weights assigned to each variable are changed. It should be noted that the initial weights specified in this study were .03, which is not large, but in a linear regression equation consisting of 68 independent variables, such a weight could be considered significant. Assigning an initial weight of .30 for each variable should have ensured that each variable was given consideration by the ANN.

The data for each company covered only 11 years and the method chosen for comparison against *NeuroXL Predictor's* output was stepwise regression using SPSS. Performing a single linear regression on all available data to obtain a single regression formula to be used in predicting 2009 results was considered. To be consistent with *NeuroXL Predictor* which was run on a company by company basis (86 times, one for each company), regression was also run on a company by company basis. This meant 946 separate regressions (one per year for 11 years) for each of the 86 companies were performed in SPSS. Therefore, 86 individual regressions had to be run each year, one for each company for data covering the years 1999-2008 in order to derive

86 regression formulas to apply to 2009 data for each of the 86 companies. To obtain an individual regression equation for a company for a specific year the model was built using the default step-wise procedure in SPSS. Each formula was then applied to each of the 86 company's independent variables. This was accomplished by creating a separate worksheet for each of the 86 companies. Each worksheet was designed to have a designated area in which to paste the regression equation derived by SPSS. Once the regression equation was entered, the worksheet calculated a prediction for that company. The absolute difference between the regression result and actual output and the absolute difference between *NeuroXL Predictor* predictions and actual output were then compared.

The method in which regression results were applied on an individual basis can be demonstrated using Appliance Recycling Center (see *Exhibit VI*). Using stepwise regression, 4 iterations of results were derived. As the regression was performed, variables were added to the model. In this case, no variables were removed, however, in other cases some variables appeared in one iteration but not the next iteration or the final iteration. The only relevant information in *Exhibit VI* is the 4th and final iteration. The final iteration was used as the actual regression formula. The statistical software package SPSS was used to derive a regression equation for each company.

5.2.3 Evaluation versus Statistical Stepwise Regression

Regression and ANN approaches are both intended to provide predictions. The only difference is that one cannot determine which variables were chosen by the ANN. It is also impossible to determine the number of iterations used by an ANN to derive its final equation.

Just as regression was performed on each company, the NeuroXL Predictor program was also applied individually to each company. In order to demonstrate how this methodology was applied, a few examples are provided below. One example (Panera Bread) was selected to see how *NeuroXL Predictor* handled a company that required 8 regression iterations. The other example (Cato Corp) was representative of a company that required a single iteration.

CHAPTER VI

Results

6.1 Results obtained from *NeuroXL Clusterizer*

6.1.1 Classification Accuracy

There is no means to ascertain with 100% certainty whether the three classifications derived from *NeuroXL Clusterizer* are the same as the true correct three classifications derived by other means. However, there is strong support that *NeuroXL Clusterizer* does in fact group companies in a similar manner to the classifications derived from other means. As shown in the following analysis, classifications derived using two-step cluster analysis could be matched relatively easy with *NeuroXL Clusterizer* classifications.

Comparing the clusters obtained using average bad debt expense to average write-offs with those obtained using *NeuroXL Clusterizer* produced the following results:

Visual Binning/*NeuroXL Clusterizer* Comparison

Time Period	Consistent	Inconsistent
1998	41	45
1998-1999	41	45
1998-2000	38	48
1998-2001	39	47
1998-2002	43	43
1998-2003	43	43
1998-2004	44	42
1998-2005	44	42
1998-2006	44	42
1998-2007	45	41
1999-2008	46	40
2000-2009	49	37
	517	515

If *NeuroXL Clusterizer* classified a company into the same cluster as the cluster obtained using average bad debt expense to average write-offs, it was categorized as consistent. If not, it was classified as inconsistent. See *Exhibit VII* for a graphical presentation of the results. *Exhibit VII* demonstrates that the ANN is learning. Initially, the results diverge a little. Then they gradually converge and eventually *NeuroXL Clusterizer* produced more consistent classifications than inconsistent classifications.

The visual binning method used subjective judgment, so the SPSS two step cluster procedure was performed on the data, which eliminated subjective judgment. The data results and corresponding graph (*Exhibit VIII)* obtained using that method are better than the results obtained using visual binning. Visual binning was not a precise statistical technique. It was in essence a sort of 'visual eye-balling' technique. Given that two-step cluster analysis is statistically-based and given that *NeuroXL Clusterizer* produced much more consistent results when compared to this technique, it can be inferred that *NeuroXL Clusterizer* is more consistent with the statistically sound method.

<u>Two-Step Cluster Analysis/*NeuroXL Clusterizer* Comparison</u>

Time Period	Consistent	Inconsistent
1998	54	32
1998-1999	54	32
1998-2000	51	35
1998-2001	54	32
1998-2002	56	30
1998-2003	54	32
1998-2004	55	31
1998-2005	58	28
1998-2006	57	29
1998-2007	58	28
1999-2008	63	23
2000-2009	60	26
	674	358

The above results provide strong support in favor of *NeuroXL Clusterizer's ability to* successfully categorize companies into similar groups based on the behavior of their bad debt expense and related allowance for bad debt. It is possible to examine certain variables and predict *how* a company will behave in regards to bad debt. The next goal is to move past generalizations and derive actual predictions.

6.2 Results obtained from *NeuroXL Predictor*

6.2.1 Prediction Accuracy

Using the methodology described above, *NeuroXL Predictor* was used to obtain predictions for each of the 86 companies in the sample. Similarly, as was previously discussed, stepwise regression analysis was also used to obtain predictions for each of the 86 companies. Running this regression for each company yielded results for 85 out of 86 companies (Ruddick Corporation was the only exception). It was unable to perform regression satisfactorily on only one company. The results of the regression versus *NeuroXL Predictor* results are listed below.

Regression/*NeuroXL Clusterizer* Comparison of Absolute Residual Differences

	NeuroXL	SPSS
Average	3.098269	7.278233
Standard Deviation	10.36628	29.7397
Min Difference	0.000609	0.004023
Max Difference	81.36172	247.2964

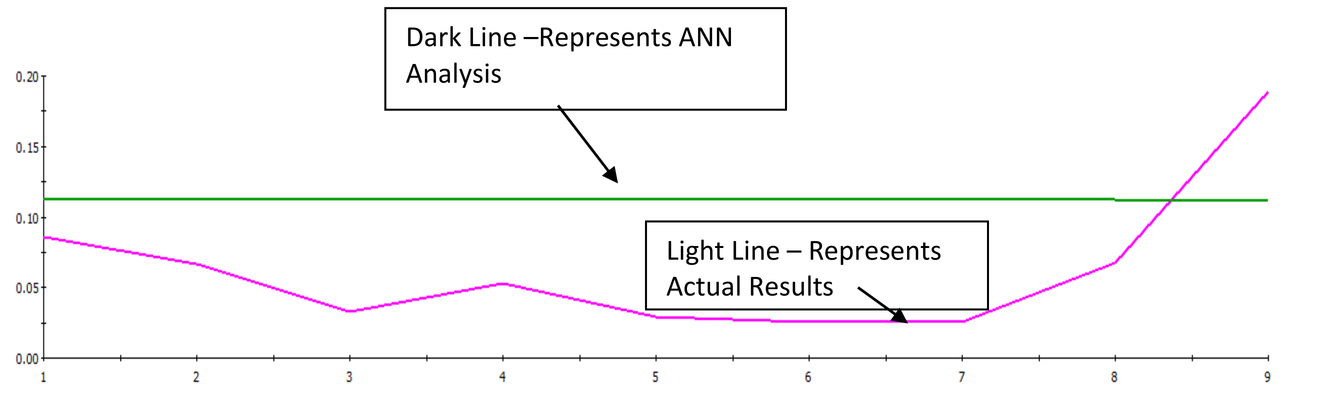
NeuroXL Predictor provided better results than ordinary regression. The amounts above refer to absolute differences. Absolute differences were used because an error that overestimated the actual amount was just as serious as an error that underestimated the actual amount.

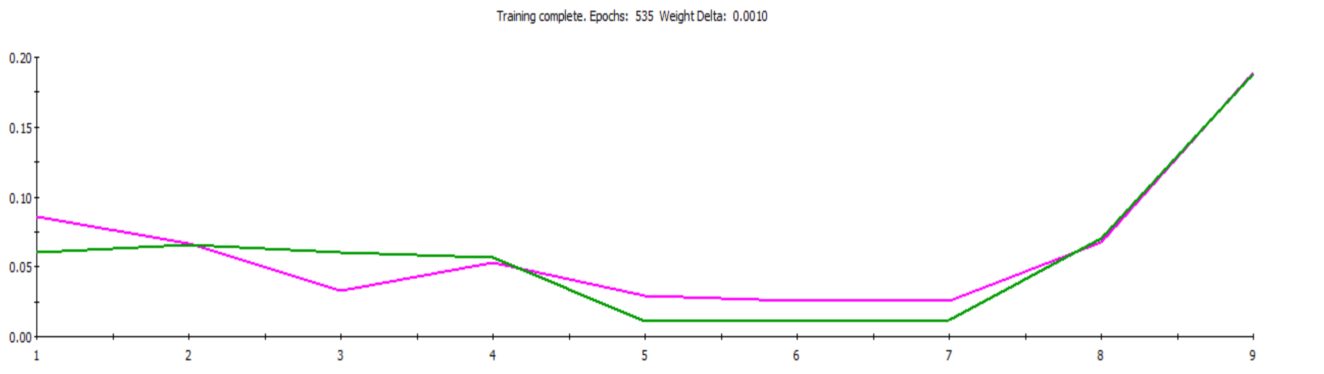
In regards to the absolute differences for *NeuroXL Predictor* and SPSS output, *NeuroXL Predicor* was, on average, the more accurate (accuracy being measured as the difference between the actual result and the predicted result). Out of 85 comparisons, the NeuroXL Predictor output was more accurate 47 times compared to SPSS, which was more accurate 38 times. The average difference between *NeuroXL Predictor* output and actual was more than one half as small as the average difference between SPSS output and actual. Also, the variability for the *NeuroXL Predictor* residuals was smaller, as its standard deviation was about a third of that of SPSS. As a result, it can be concluded that *NeuroXL Predictor* is in fact able to derive accurate estimates regarding bad debt expense and the related allowance for bad debt using numerous ratios and financial statement data. However, that does not prove it is better from a statistically significant standpoint.

<u>PANERA BREAD CO – Used 8 iterations for Backwards Propagation Regression</u>

Actual Ending Allowance for Bad debt	Neuro-Predictor Prediction	SPSS Regression Prediction
0.125	0.202318996	0.091821859

-





The graph above represents *NeuroXL Predictor* interface. The light colored line above represents the actual ending allowance for bad debt amounts for each year. The dark line is a preliminary fit. The ANN starts with no understanding and then ‘learns’ as it is given more data to process. At this point, ten years of independent variables and the associated dependent variable have been specified using the *NeuroXL Predictor* interface. In addition, the independent variables for the 11th year have been specified as well, but not the actual result (i.e., dependent variable). Using this information, the *NeuroXL Predictor* program 'learns' and begins to fit the dark line to the light line as it analyzes the data.

As can be seen above, the dark line did not fit the light line perfectly. It is representative of the *NeuroXL Predictor* best estimate. The output provided by this program was a numerical prediction. A comparison of the actual amount, the amount predicted by *NeuroXL Predictor* and the amount derived from the regression equation for Panera Bread Co. are below:

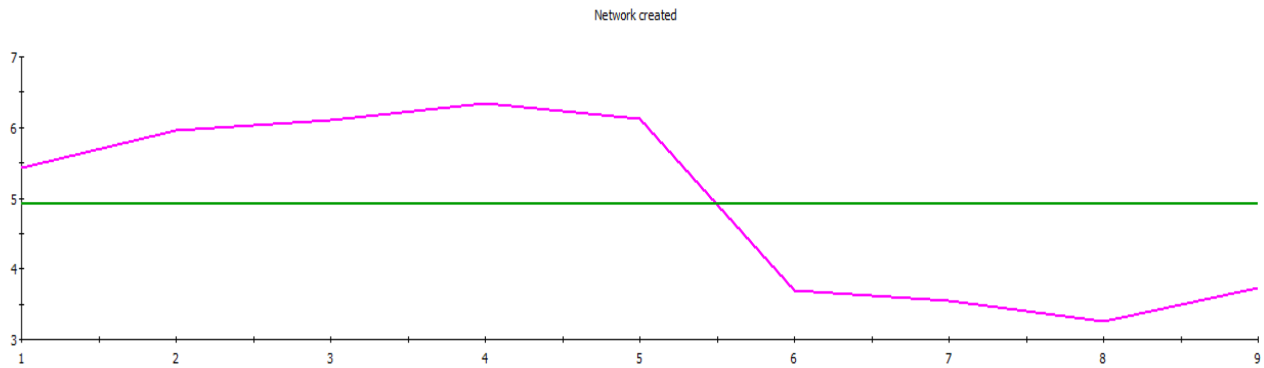
Actual Ending Allowance for Bad Debt Accounts: 0.125

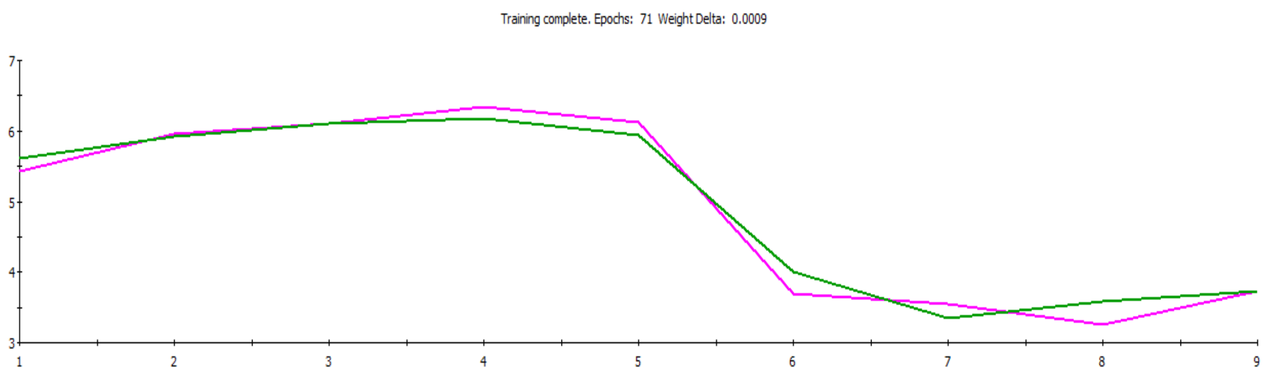
NeuroXL Predictor Prediction: 0.202318996

SPSS Regression Prediction: 0.091821859

In this situation, regression (i.e., SPSS) provided the more accurate estimate. The method illustrated above was performed on every company in the sample. Sometimes the *NeuroXL Predictor* line closely matched the actual line. An example of that is provided below:

CATO CORP -CL A – Used 1 iteration for Backwards Propagation Regression





In this instance the dark line is a much closer match than the Panera Bread Company example and it provided a more accurate estimate as demonstrated by the data below:

Actual Ending Allowance for Bad Debt Accounts: 0.003

NeuroXL Predictor Prediction: 0.06308333

SPSS Regression Prediction: 0.085030253

In this situation, *NeuroXL Predictor* provided the more accurate estimate.

Paired two sample for means t-tests were performed. In addition scatterplots pertaining to each of the means t-tests were also derived in order to gain preliminary expectations of statistical significance. A graph of the absolute values derived by *NeuroXL Predictor* and SPSS demonstrated many of the predictions were close (see *Exhibit IX*). The graph contains a few outliers and does not indicate any significant differences between *NeuroXL Predictor* and SPSS. The scatterplot for residual amounts (see *Exhibit X*) demonstrated less variability than the scatterplot for absolute values (meaning a lower likelihood of finding statistically significant results). The first two graphs and their individual means t-tests were derived using the same data, which eliminated several noticeable outliers (Target, CVS, MEDCO, and Nordstrom). After eliminating those outliers, a clearer picture emerged as to the nature of prediction accuracy. The final scatterplot (see *Exhibit XI*) was derived using the absolute percentage differences between actual amounts and those predicted by *NeuroXL Predictor* and SPSS. *Exhibit XI* was similar to *Exhibit X* in that both indicated a lot of variability.

The motivation for comparing an ANN prediction against a prediction derived from conventional statistical analysis was to prove that the ANN performed better, providing more accurate estimates than statistical methods. As a result this study examined the following hypotheses:

$$\mathbf{H_0}: \mu_{\text{Regression Error}} - \mu_{\text{Neuro Error}} <= 0$$

$$\mathbf{H_A}: \mu_{\text{Regression Error}} - \mu_{\text{Neuro Error}} > 0$$

A paired two sample for means t-test was conducted to evaluate the predictive accuracy of the residuals yielded by *NeuroXL Predictor* and the residuals yielded by SPSS. There was no statistically significant difference between *NeuroXL Predictor* residuals. The residuals test suffered from one major weakness, which was the inclusion of companies of varying sizes. This made comparisons problematic at best. A large difference between predicted and actual often resulted because of the magnitude of the numbers associated with large companies. Thus, a large difference between predicted numbers and actual results may be significant for a smaller company, but not material for a larger company.

In order to evaluate the results and eliminate the effects of company size, the differences between actual and predicted were evaluated in terms of absolute error amounts and absolute percentage error amounts. This made it possible to compare companies of different sizes. Thus, a large difference pertaining to a large company, could equate to a relatively small difference when evaluated in terms of absolute differences and/or percentage differences between actual and predicted. The elimination of size provided a means to more accurately determine true predictive accuracy as predictions would be based upon a common measure. A comparison of accuracy expressed as absolute differences and as percentage differences demonstrated that there is a statistically significant difference between *NeuroXL Predictor* and SPSS predictions.

A second two sample for means t-test was conducted to evaluate the predictive accuracy of the absolute differences between the predictions provided by *NeuroXL Predictor* and actual results and SPSS and actual results. *NeuroXL Predictor* absolute differences (M = 1.4860, SD = 2.448) and SPSS absolute differences (M = 2.023, SD = 3.486), t(80) = -1.5687. The p-value was .0603 (one-tailed). The mean difference in the predictions was -.5368 with a left tail critical value of -1.2179 (at the 95% confidence interval). Since the test statistic was within the reject region, the null *was* rejected at this significance level.

The analysis for absolute percentage differences was applied to all the companies in the original sample except for the one company that yielded no regression results. The companies which did not yield percentage amounts (Burlington and Eye Care), and a few companies which were classified as outliers (Pantry, Caribou, Famous Daves, Einstein, and Appliance Recycling) were also excluded from the ananlsis of absolute percentage differeces. The resulting graphical depiction can be seen in *Exhibit XI*.

A paired two sample for means t-test was conducted to evaluate the predictive accuracy of the percentage differences yielded by *NeuroXL Predictor* and SPSS. There *was* a statistically significant difference between *NeuroXL Predictor* percentage differences (M = .4180, SD = .3912) and SPSS Percentage Differences (M = .5538, SD = .6033), t(77) = -2.2037. The p-value was .01523 (one-tailed). The mean difference in the predictions was -.1358. The left tail critical value was -.2586. Therefore, for this test, the null hypothesis was rejected at the 95% confidence interval.

Upon further analysis, it was also determined that for this data, the null was also rejected at the 99% confidence interval. At this confidence interval the left tail critical value was -.2986. Using the same t-statistic, the null hypothesis *was* rejected again. Therefore, there is strong support for arguing *NeuroXL Predictor* provides better predictions than regression analysis using SPSS.

CHAPTER VII

Discussion

7.1 Summary and Conclusions

The ultimate evaluation of the artifact is determined by whether it provides an estimate of bad debts that more closely approximates the actual book value than conventional methods. The artifact was given sufficient historical data to 'learn' about the inputs which ultimately have a bearing on the allowance for bad debt. Since historical data exists in regards to the accuracy of the allowance for bad debt, the artifact is evaluated based on whether it provides better results (i.e. provides an estimate of allowance for bad debt which is more accurate than the actual historical estimate) than conventional methods.

The performance of *NeuroXL Clusterizer* proved to be reasonably accurate in regards to the results provided by Two-Step Cluster analysis. The main benefit of using *NeuroXL Clusterizer* is to gain preliminary expectations. The accuracy demonstrated by the program, when its results were compared to Two-Step Cluster Analysis proved that it is possible to quickly obtain a reasonable classification regarding a particular factor (in this case, the allowance for bad debt) without having to carry out tedious and multiple statistical analyses. A total of 86 companies were included in the analysis and each company was subjected to multiple tests to evaluate its classification. This resulted in 1032 individual classifications. Of those classifications, the cluster derived using two-step cluster analysis and the cluster predicted by *NeuroXL Clusterizer* differed by two only 11 times.

Thus, it can be inferred that *NeuroXL Clusterizer* is capable of providing reasonably accurate snapshot classifications.

The results indicate that *NeuroXL Predictor* appears to be the better approach when compared to regression. The average difference was lower, implying better accuracy and the standard deviation was much lower, implying less risk. Companies of different sizes were included in the sample, however, the worst result provided by *NeuroXl Predictor* was much better than the worst result provided by regression.

Both *NeuroXL Clusterizer* and *NeuroXl Predictor* proved to be user friendly applications that worked seamlessly with Microsoft Excel. Given the results of this study, it could be argued that any company in the sample would be willing to pay $150 (the cost of both packages combined) to use these programs. The potential of these programs seem to outweigh their costs.

7.2 Future Research

Just a few years ago the use of ANNs would not have been explored by many companies. Such a project would have required a great deal of programming and the costs versus benefits would have been hard to justify. It is reasonable to expect that usage of ANNs in the future will be a necessity.

According to Wilkins (2010), 800 billion gigabytes of data was created in 2009. That is a lot of data, but by 2020, it is estimated that approximately 35 trillion of gigabytes will be created (Wilkins 2010). The level of exponential growth in data generated will be far beyond the capacity of human beings to process by 2020. It would be virtually impossible for a human being or even a group of human beings to find discernible patterns in such large amounts of data. ANNs will be invaluable because they can analyze huge amounts of data unlike a human being. At the current rate of growth, humans will gradually become overwhelmed unless they employ ANN systems.

Currently, ANN systems are already being employed by many retail chain stores when it comes to inventory. Every item added to and removed from a store's inventory is immediately recorded in a database. For example, if you go to your local retail drugstore and buy office supplies, that purchase is deducted instantly in a centralized database at company headquarters. As items are sold, there is a threshold at which the computer will initiate an order to restock different inventory items. These decisions are based on patterns and predictions and such an ANN may be utilized to make optimal decisions.

With regards to inventory as well as other items which independent auditors must examine, the benefits of using ANNs are not hard to imagine. Given the high importance of an independent audit being accurate (because investors rely on them to make investment decisions), an ANN approach to audits is definitely in order. For now, traditional audit techniques would have to be used (they simply can't be abandoned until an ANN proves to be accurate and reliable), but if ANNs are gradually incorporated into the audit process, it would increase the likelihood that fraud may be detected more frequently and at earlier stages. Since ANNs are designed to look at patterns and analyze them, it is only logical that they may detect problems that an ordinary audit would not.

While the independent audit profession would benefit from ANNs, it will take time to integrate them into the process. It is incumbent upon the accounting profession, especially auditors, to take advantage of the benefits offered by ANNs. At the very least, auditors could continue to rely on traditional methods while at the same time incorporating the use of ANNs. As time passed, and as auditors gained confidence with ANN accuracy, it may force firms to re-evaluate how they conduct audits. Rather than using variations of a basic set of workpapers year after year, which could lead to a lack of vigilance, auditors may be forced to do a complete re-evaluation of their audit techniques.

In regards to auditing, it should be noted that ANNs may not be the best technique. Gaganis (2009) notes that while a lot of studies have been conducted involving ANNs and audits, only a few have considered the usage of what he calls Probabilistic Neural Networks (PNN). A PNN has an advantage over the traditional ANN because it incorporates traditional statistical methods along with traditional ANN functions. This means that a PNN is able to provide a better explanation of its results than an ANN.

In summary, it is easy to envision that a company might use multiple ANNs. For chief executives and upper management, these tools could come to represent an invaluable competitive advantage. If a large company, with many divisions and facets employed ANNs on a widespread basis throughout the company, the information could be delivered to decision-makers in the form of a dashboard. Hypothetically, this has unlimited potential. Depending on the type of data, an ANN may be operating with up-to-date information most of the time. Some data may take longer to accumulate, but as technology grows at an exponential rate, the amount of data available in real-time will grow at the same rate. Thus, a top management person could have a dashboard that not only provides instantaneous information, but also one that makes suggestions and/or decisions through an ANN process.

The scenario envisioned above would almost certainly entail the usage of much more sophisticated and costly ANN programs than the ones used in the present study. The prime difficulty facing the development of such a network would be the selection of variables. Future research needs to address methods for ANNs to gather their own independent variables, both from internal and external sources. The ANNs used in the present study were not capable of gathering their own variables. However, the complexity of the problems for this study did not necessitate ANNs capable of data gathering. The real challenge facing any company trying to implement and maintaining an ANN will almost surely involve automated data collection. Given the exponential growth in data, not only will the amounts of information exceed human capacity to analyze and recognize patterns, it will also exceed human capacity to sort through enormous amounts of variables. Thus, data collection will prove to be a major area of research in regards to ANNs and their usage.

CHAPTER VII

Limitations

This study focused on only one item listed in the financial statements (Allowance for Bad Debt). The results obtained from an Allowance for Bad Debt focus were favorable. However, this particular item lends itself to evaluation. There are numerous items which could have been investigated. Some of these items lend themselves to easy classification. Others do not. The favorable results obtained from an Allowance for Bad Debt focus may not be replicated when other items are studied. As a result, this study can only make inferences about the Allowance for Bad Debt.

In addition, only one industry sector (retail) was represented. The results for other industry sectors may differ. Also, since only one SIC category was represented, it is unknown whether an analysis, which includes a combination of companies from different SIC codes, would provide accurate classifications.

As other studies have demonstrated in the past, this study also provided evidence that *NeuroXL Predictor* (i.e. ANN) provides superior estimates to traditional regression analysis. However, like other ANNs, *NeuroXL Predictor* is unable to provide the specific weights it assigns to different independent variables. The variables selected by SPSS were easily discernible (see *Table 2*).

These results indicate that the set of independent variables chosen in the study actually had an impact on the Allowance for Bad Debt from a traditional statistical approach. This study used a method of dependent variable selection that attempted to be as 'all-inclusive' as possible. In other words, the main goal was to use a large volume of independent variables and then apply them on a company by company basis in order to obtain reliable predictions. Each company is different and it was not expected their individual regression equations would be identical in terms of the independent variables chosen. The study indicates that fifty two variables (see above) were used. Only 8 variables were not used (see *Table 3*).

It is impossible to know how the inclusion of these variables impacted the ANNs used in this study. Given that these networks mimic the human brain, it is entirely possible that the inclusion of some variables may have 'confused' the ANN. Certainly, if a variable had no impact on the overall prediction, the ANN would have eventually eliminated it as it accumulated data and results. However, if the variable had never been included at all, it may have led the ANNs to make more accurate predictions sooner. One way to determine a variable's impact would be to compare the results obtained when the variable is included with results obtained when the variable is not included.

ANNs produce output. They do not produce a regression equation. As a result one cannot determine the importance placed on individual variables. Thus, any explanation of why ANNs are superior predictors when compared to the traditional approach is difficult to explain due the activities which have occurred in the hidden layer of the ANN process. It should also be noted that *NeuroXL Predictor* can also be adjusted. Some of these adjustments may result in superior predictions for some companies while resulting in less accurate predictions for others. The focus of this study was on a group of companies. As a result, the nuances of individual companies were not a priority. It is highly probable that if an individual company used the ANN approach as this study, they would have selected different variables and tailored the ANN to meet their own needs. Such a detailed analysis on a company by company basis was beyond the scope of this study.

This study used 68 independent variables. Undoubtedly, each variable had a different impact on each company. A consideration of the variables best suited to each specific company was beyond the scope of this study. However, given the research results, one could easily apply *NeuroXL Predictor* in conjunction with variables the individual variables deemmost relevant to the specific company to generate a more reliable estimate of the allowance for bad debt.

Currently, the major limitation of ANNs, or at least the ones used in this study was the fact that the independent variables had to be defined by a human being. Consequently, the ANN cannot be viewed as a completely unbiased mechanism. Its predictions are connected to the variables it is instructed to analyze. Some variables may be completely appropriate, while others may not. Furthermore, important variables may be omitted.

Unfortunately, nothing can be done about the past. However it is incumbent upon the accounting profession, especially auditors, to take advantage of the benefits offered by ANNs. At the very least, auditors could continue to rely on traditional methods while at the same time incorporating the use of ANNs. As time passed, and as auditors gained confidence with ANN accuracy, it may force firms to re-evaluate how they conduct audits.

In this study, the *NeuroXL Predictor* was trained using 10 years of data to predict a value in the 11^{th} year. Additional insight could be gained into both the accuracy and learning ability of this program if a progressive approach had been taken. For example, the third year could be predicted based on the first two years, the fourth year could be predicted on the first three years, etc. In actuality, there were many combinations in regards to the amount and types of data given to the ANN to learn. Valid justifications could also be made for each. This study built upon data, so the end result was a large data set from which the ANN could learn. However, there is the concern that older data may lose relevancy over time, which means that ANNs may be more accurate in some instances if given data covering a shorter period rather than longer periods from which to learn.

The present study did not incorporate audit opinions as a variable, but it could be modified to do so. Therefore, another extension of the present study would be to determine audit accuracy and fraudulent behavior. The investing public at large would benefit if properly developed and tested ANNs could act as a constant audit oversight. Financial markets suffer when it is discovered that financial statements contain inaccurate numbers. However, ANNs provide a method to identify suspicious activity almost instantaneously. This would act as a deterrent for those who are inclined to engage in fraudulent activity.

The ANN packages used in this study are just one brand of ANN software. If another brand were used, different results may be obtained. It should also be noted that many aspects of a company could be examined in a similar fashion as was done in this study. For example, a similar study could be performed on Net Income, Cash Flows, etc… Virtually any aspect of a company could be examined using ANN.

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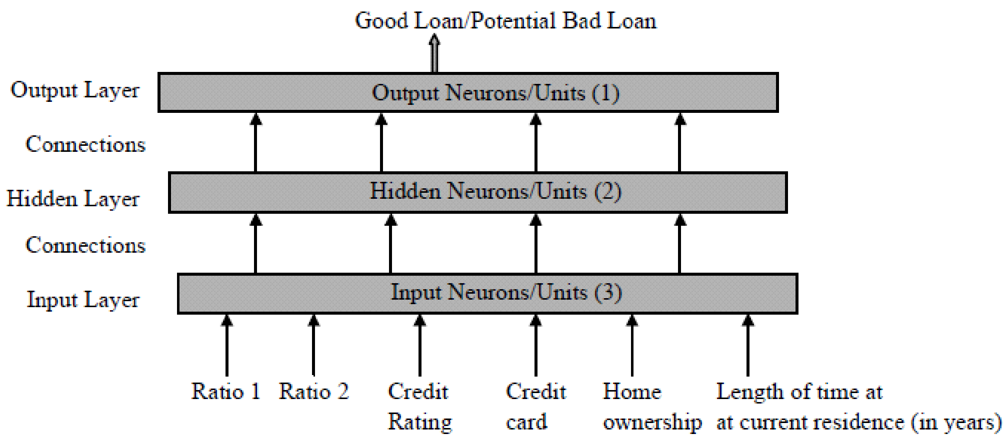
Exhibit I: Schematic of a Back-Propagation Network (Malhotra & Malhotra, 2003)



1. The number of output neurons correspond to the number of output variables
2. The number of hidden neurons can vary and correspond to the most efficient neural network model
3. The input neurons correspond to the number of input variables

Exhibit II: Example of *NeuroXL Clusterizer* as used in the Present Study

SIC Code	Name	Accounting Average Tax Rate	Accounts Receivable Turnover	Acid Test (Quick Ratio)	Advertising Expense	Cash / Current Liabilities	CashFlow-Assets-PreTax / Interest	Common Stock Return - Fiscal Year
5912	RITE AID CORP	.280	27.828	.226	.000	.022	-2.347	83.900
5311	SEARS HOLDINGS CORP	.307	.000	.192	443.000	.192	.000	278.525
5411	SUPERVALU INC	.395	42.409	.275	.000	.005	.000	50.000
5331	TARGET CORP	.382	19.278	.378	745.000	.050	2.895	256.000
5912	WALGREEN CO	.388	40.873	.327	60.000	.031	114.612	90.000
5331	99 CENTS ONLY STORES	.390	157.119	2.400	.000	2.277	41.908	4.433
5940	BARNES & NOBLE INC	.410	59.293	.115	.000	.040	4.682	29.200
5940	BOOKS-A-MILLION INC	.380	19.560	.174	.000	.036	2.076	4.500
5812	EINSTEIN NOAH RESTAURANT GRP	.000	8.633	.754	.000	.476	.987	.532
5990	EMERGING VISION INC	.000	3.565	.552	.000	.062	-.450	.476
5990	EYE CARE CENTERS OF AMERICA	.000	39.072	.262	23.816	.116	.191	3.500
5812	FAMOUS DAVES OF AMERICA INC	.000	.000	.504	.000	.504	-107.671	1.050
5900	FERRELLGAS PARTNERS -LP	.000	11.924	.604	.000	.153	2.093	4.325
5940	GOLFSMITH INTL HOLDINGS INC	.000	.000	.000	.000	.000	.000	.000
5990	HEARUSA INC	.000	7.486	1.815	4.105	1.281	-163.726	.300
5912	MEDCO HEALTH SOLUTIONS INC	.000	.000	.000	.000	.000	.000	.000

Exhibit III: Assignment of Companies to Clusters using *NeuroXL Clusterizer* (Present Study)

Name	Cluster
RITE AID CORP	3.000
SEARS HOLDINGS CORP	3.000
SUPERVALU INC	3.000
TARGET CORP	3.000
WALGREEN CO	3.000
99 CENTS ONLY STORES	2.000
BARNES & NOBLE INC	2.000
BOOKS-A-MILLION INC	2.000
EINSTEIN NOAH RESTAURANT GRP	1.000
EMERGING VISION INC	1.000
EYE CARE CENTERS OF AMERICA	1.000
FAMOUS DAVES OF AMERICA INC	1.000
FERRELLGAS PARTNERS –LP	1.000
GOLFSMITH INTL HOLDINGS INC	1.000
HEARUSA INC	1.000
MEDCO HEALTH SOLUTIONS INC	1.000

Exhibit IV: Example of *NeuroXLPredictor* as used in the Present Study

Name	Year	Selling, General & Admin. Expenses	Total Debt / Total Assets	Umemployment Level - Looking for Full-Time Work (in thousands)	Unemployment Level (25-54 years old) in thousands	Receivables - Estimated Doubtful 1998	Bad Debt Expense	Write-off	Receivables - Estimated Doubtful	NeuroPredictor Output	
BUCKLE INC	1999	0.025628052	74.977	0.177722	4520	3018	0.3	1.095	0.117	0.225	0.2336135
BUCKLE INC	2000	0.029742121	80	0.1581856	4539	3065	0.225	0.858	0.833	0.25	0.2405367
BUCKLE INC	2001	0.030974775	80.725	0.1169627	6893	4745	0.25	0.816	0.816	0.25	0.2341469
BUCKLE INC	2002	0.030726076	85.733	0.1171714	7351	5022	0.25	0.856	0.889	0.217	0.2198864
BUCKLE INC	2003	0.037737099	94.713	0.1751071	6997	4929	0.217	0.769	0.805	0.181	0.1765726
BUCKLE INC	2004	0.03472439	107.607	0.1790562	6538	4518	0.181	0.379	0.447	0.113	0.1297273
BUCKLE INC	2005	0.035148603	117.716	0.1989841	5870	4161	0.113	0.319	0.338	0.094	0.1048727
BUCKLE INC	2006	0.036542068	128.293	0.2216498	5520	3754	0.094	0.238	0.26	0.072	0.0764457
BUCKLE INC	2007	0.03288336	144.911	0.2492738	6214	4245	0.072	0.328	0.338	0.062	0.0560552
BUCKLE INC	2008	0.02749714	184.255	0.2753213	9662	6692	0.062	0.276	0.292	0.046	0.0468744
BUCKLE INC	2009	0.027981035	201.157	0.2754002	13370	9184	0.046	0.358	0.369	0.035	0.0365566

Exhibit V: *NeuroXL Predictor* Training

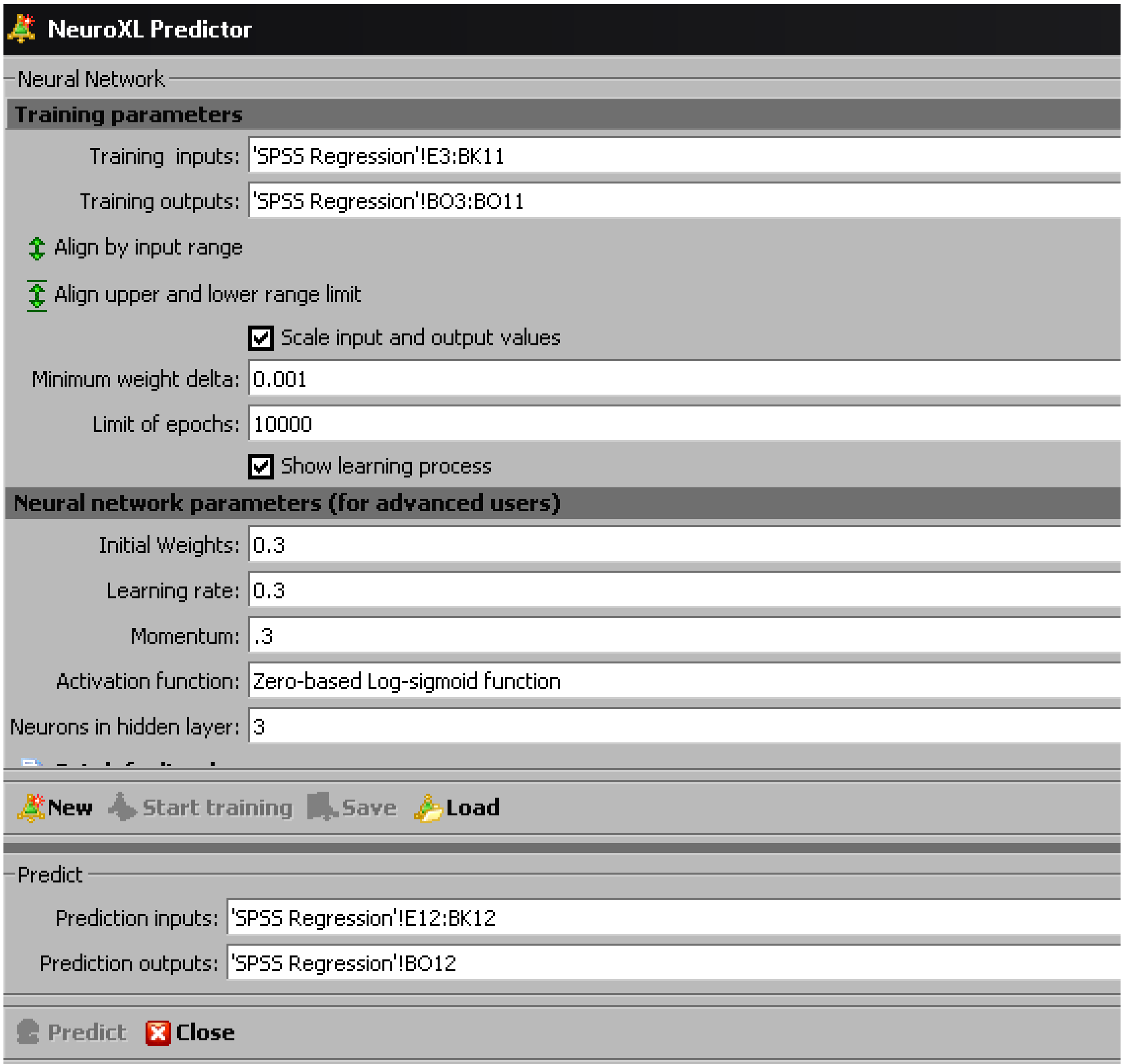


Exhibit VI: SPSS Regression Output for 4 Iterations (Appliance Recycling Center)

Coefficientsa,b

Model		Unstandardized Coefficients
		B
1	(Constant)	-67.04596
	Year	0.03352
2	(Constant)	-63.63893
	Year	0.03181
	PricedivSalesPrimary	-0.00080
3	(Constant)	-49.33322
	Year	0.02466
	PricedivSalesPrimary	-0.00097
	IncomeTaxesdivSales	-7.51779
4	(Constant)	-96.52818
	Year	0.04828
	PricedivSalesPrimary	-0.00095
	IncomeTaxesdivSales	-6.32664
	AdvertisingExpense	-0.04903

Exhibit VII: Graphical Presentation of *NeuroXL Clusterizer* Results versus Average Bad Debt Expense/Average Write-Off Ratios

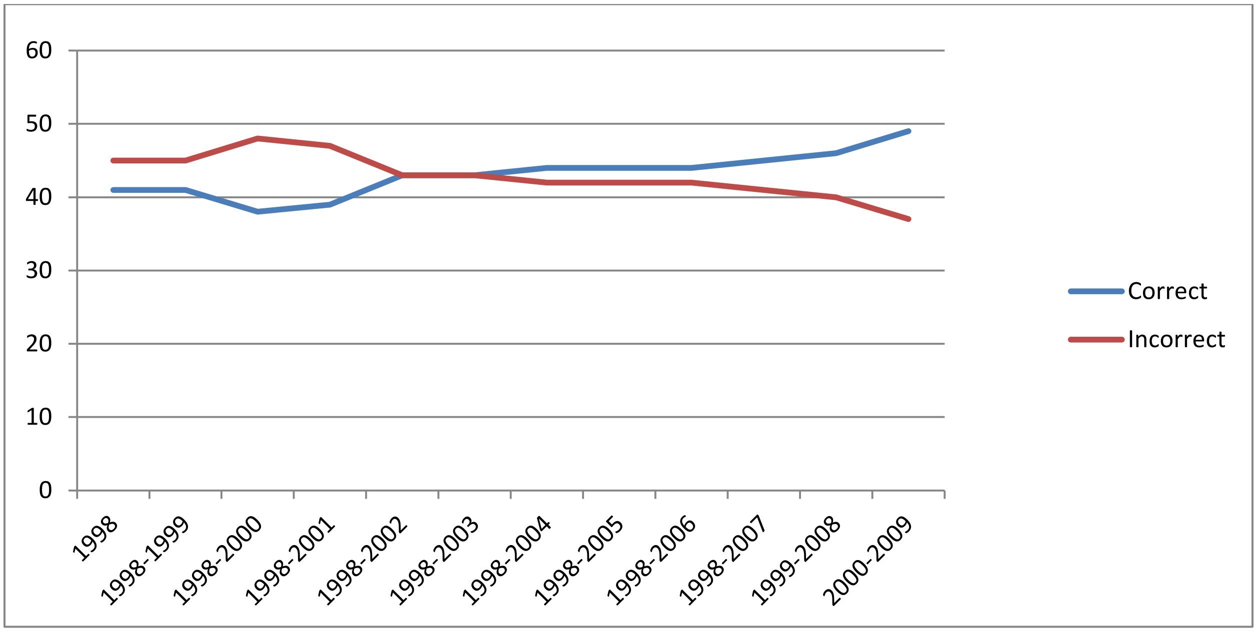


Exhibit VIII: Graphical Presentation of *NeuroXL Clusterizer* Results versus Two-Step Cluster Analysis

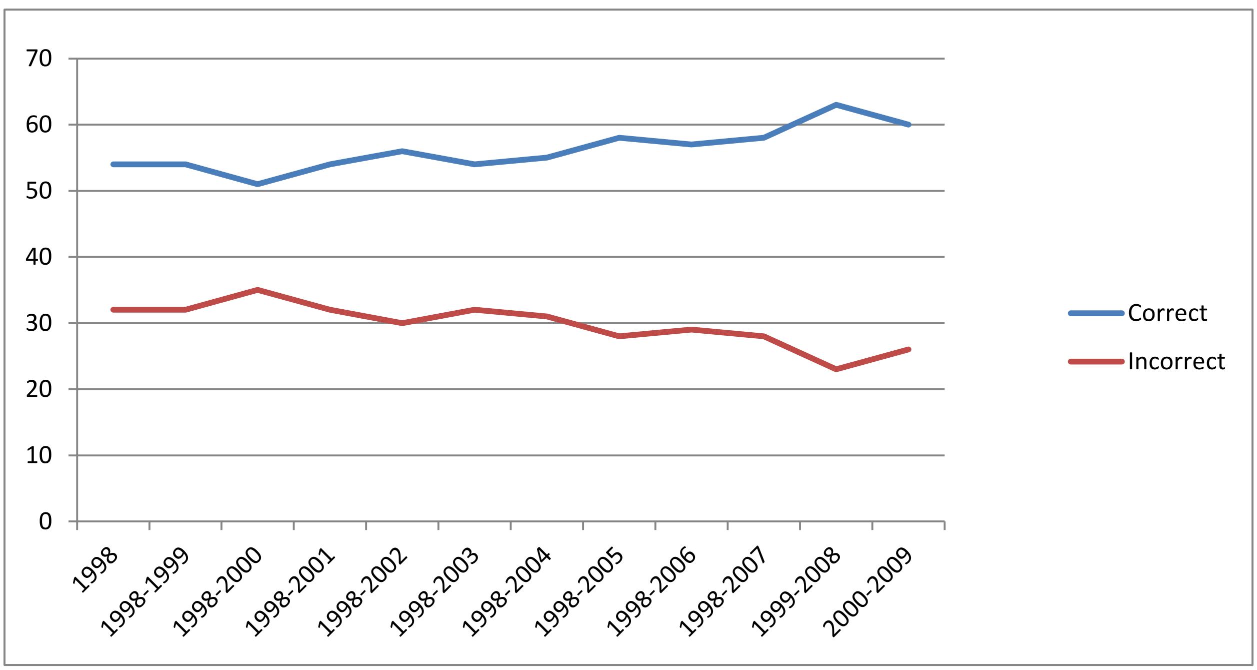


Exhibit IX: Comparison of Absolute Differences: *NeuroXL Predictor* and SPSS

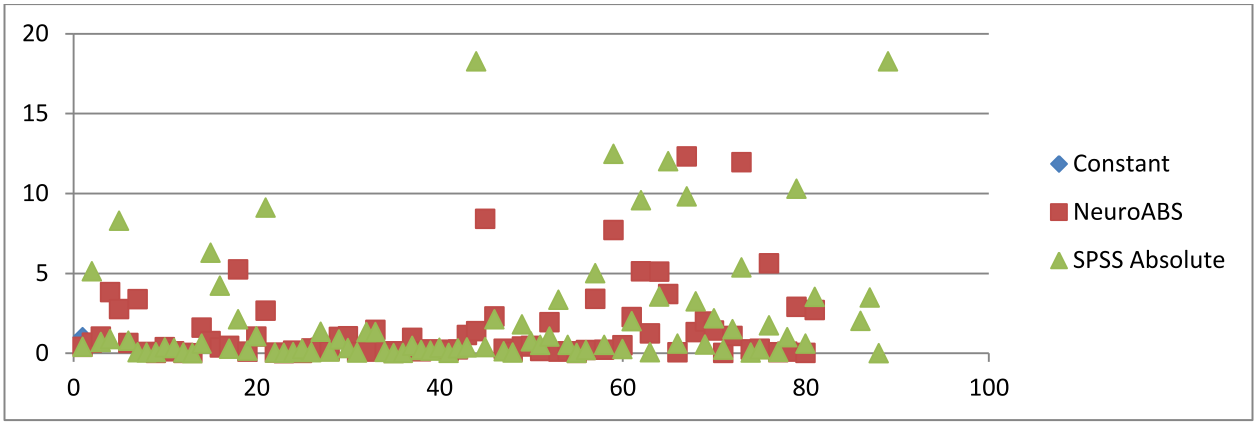


Exhibit X: Comparison of Residual Differences: *NeuroXL Predictor* and SPSS

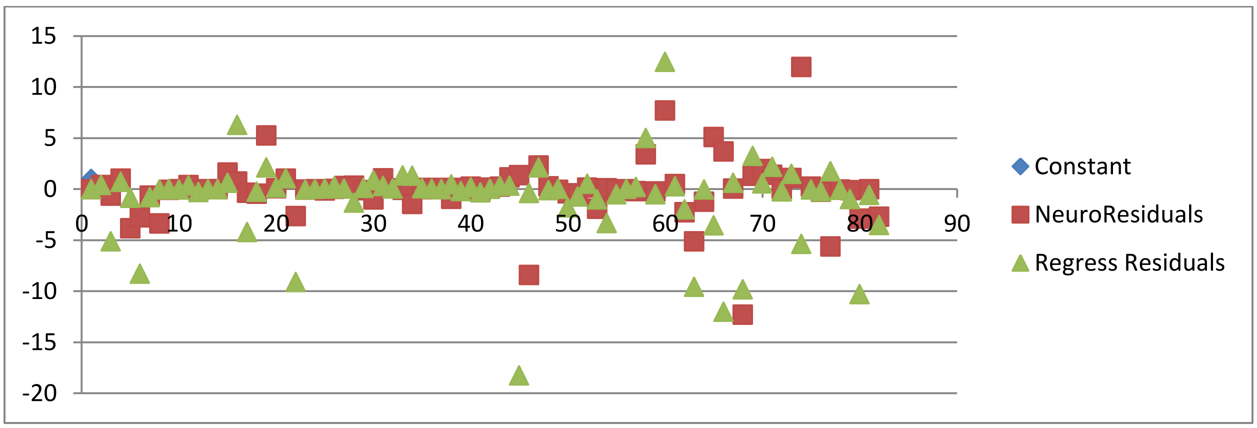


Exhibit XI: Comparison of Percentage Differences: *NeuroXL Predictor* and SPSS

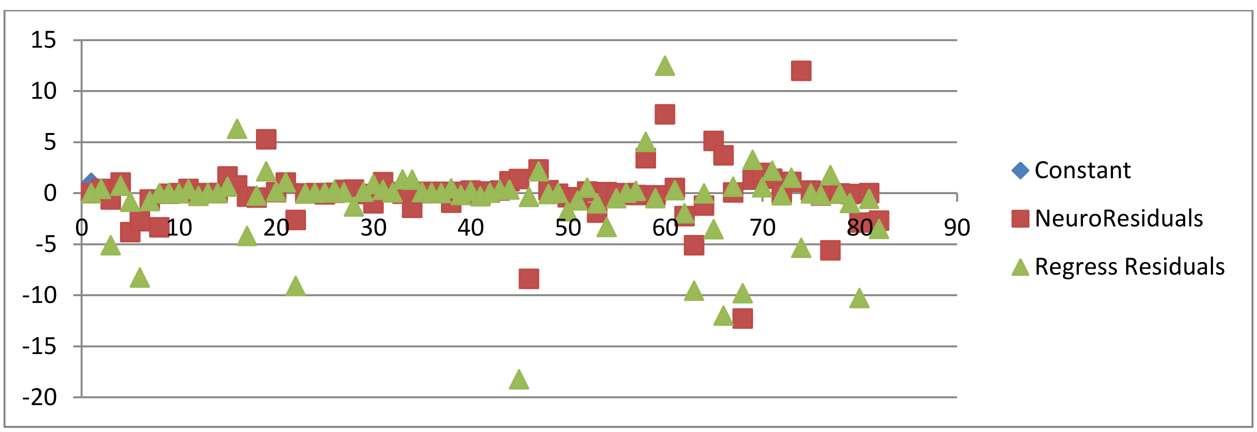


Table 1: Iterations

1	Iteration: 25 companies
2	Iterations: 22 companies
3	Iterations: 19 companies
4	Iterations: 7 companies
5	Iterations: 3 companies
6	Iterations: 1 companies
7	Iterations: 0 companies
8	Iterations: 7 companies

Table 2: Variables used by SPSS Backwards Propagation

Independent Variable	Times Used
AccountingAverageTaxRate	5
AccountsReceivableTurnover	4
AcidTestQuickRatio	2
AdvertisingExpense	7
BankCreditatAllCommercialBanksBillions	2
CashdivCurrentLiabilities	3
CashFlowAssetsPreTaxdivInterest	4
CivilianUnemploymentThousandsofPersons	6
CommonStockReturnFiscalYear	2
ConsumerBankruptcyFilings	7
ConsumerCreditOutstandingMillions	6
ConsumerPriceIndexAllItemsAnnualAvg	1
CorporateBondYield	8
CostofGoodSold	4
CostofGoodsSolddivSales	6
CurrentAssetsdivCurrentLiabilities	5
DaysSalesinAccountsReceivable	7
DaysToSellInventory	3
DepreciationandAmortizationsdivSales	4
DividendsCashCommon	2
DividendsCashPreferred	4
DowJonesIndustrialAverage	7
Employeesnumof	7
IncomedivSales	5
IncomeonAssetsdivSales	8
IncomeTaxesdivSales	6
IncomeTaxesTotal	2
InterestExpense	7
InventoriesTotal	4
InventoryTurnover	3
ManufacturersShipmentsandInventoriesMillions	6
MktValEquitydivBookValEquity	7
NETINCOMELoss	1
OperActivitiesNetCashFlow	4
PersonalSavingBillions	5
PriceCalendarYearClose	3
PricedivCommonDividends	3
PricedivEarningsPrimary	3
PricedivOperatingCashFlowPrimary	8
PricedivSalesPrimary	3
RandDdivSales	1
ReceivablesEstimatedDoubtfulPriorYr	6
ReceivablesTotalNet	9
RetainedEarningsNetOther	4
ReturnonCommonEquity	1
ReturnonEquitydivReturnonAssets	4
ReturnonTotalAssets	4
SalesdivAvgTotalAssets	3
SalesNet	2
TotalDebtdivTotalAssets	4
UmemploymentLevelLookingforFullTimeWorkinthousands	3
UnemploymentLevel2554yearsoldinthousands	6

Table 3: Variables Not Included in any Regression Formula

1) DisposablePersonalIncomeBillions
2) EPSDilutedExclEIandDO
3) EPSDIlutedInclEIandDO
4) InterestExpensedivSales
5) OperatingCashFlow
6) PersonalConsumptionExpendituresBillionsand
7) RealGrossDomesticProductBillions
8) ResearchandDevelopmentExpense

Appendix A – Sample Letter from Certegy

Dear Ms. XXXXX,

This letter is written in response to your inquiry regarding our recent inability to authorize your check. Initially, we want to assure you that we understand the concern this can cause, and we apologize for any inconvenience you may have experienced.

Certegy Check Service (CCS) is a check authorization service. Our clients throughout the United States utilize the service to help reduce losses incurred through retail practice of check acceptance. For many CCS clients we assume liability should an authorized check subsequently be dishonored. CCS maintains a computerized file containing both returned check information and driver's license or checking account number. In addition to this information, over 40 years of check authorization and resulting loss experiences CCS has developed guidelines for authorizing acceptance of checks. Our system determines the potential risks associated with checks. Many proprietary factors are evaluated and in making decisions for check approvals. We also track check writing based on many factors, including check sequence number,, check writing activity and check amounts. This process is designed to protect consumers and retailers and to prevent unauthorized individuals from writing checks on otherwise valid accounts. Unfortunately, valid check writing patterns can occasionally overlap with these patterns resulting in our inability to authorize a valid check such as yours.

Regarding our inability to authorize your check, although there were no returned checks on file, the check fell outside of approval guidelines. Unfortunately, we did not have any additional information at the time to override the concern, and we again sincerely apologize.

In closing, we do appreciate and understand your concerns. Please contact our Customer Care Department at 800-352-5970 if we can be of further assistance.

Sincerely,

CERTEGY CHECK SERVICES, INC. Customer Care Department

Source: http://consumerist.com/2008/04/certegy-decides-whether-or-not-kmart-will-accept-your-check.html

Appendix B – Abstract

A NEURAL NETWORK APPROACH TO ESTIMATING THE ALLOWANCE FOR BAD DEBT

By Donald Thomas Joyner, Ph.D.

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

Virginia Commonwealth University, 2011

Major Director: Dr. Ruth W. Epps, CPA   Department of Accounting

Appendix C - VITA

Donald Thomas Joyner was born on March 28, 1972, in Hampton, Virginia and has resided in Poquoson, Virginia his entire life. He graduated from Poquoson High School in 1990. He graduated with a Bachelor of Science in Accounting (Summa Cum Laude) from Christopher Newport University in 1994. He then received a Master of Business Administration degree from The College of William and Mary in 1996. Upon graduation from William and Mary, Donald embarked on a career in accounting, starting as a staff accountant for a small CPA firm and eventually working his way up to Chief Financial Officer of a local credit union. He was also twice elected Treasurer of the City of Poquoson. In addition, Donald has earned the CPA credential as well as many other accounting credentials.

Donald has been happily married to his beloved wife Dottie for almost 10 years. The couple has a 4 year old daughter, Adriana.