Application of Artificial Neural Networks in Business Applications

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Abstract: With the advancement of computer and communication technologies, the whole process of doing business has undergone a massive change. More and more knowledge based systems have made way into a large number of companies. Knowledge management coupled with advanced Artificial Neuro-Computing has become critical components of business intelligence. In this paper, we describe the basics of neural networks as well as a review of work done in applications of Artificial Neural Networks in several business processes.

Keywords: Artificial, Neural Networks, backpropogation, BI, DSS

Since the advent of computer intelligence, the art of doing business have undergone dramatic changes. More and more knowledge based systems have made way into a large number of companies. Knowledge management coupled with advanced Artificial Neuro-Computing has become critical components of business intelligence. In this paper, we describe the basics of neural networks as well as a review of work done in applications of Artificial Neural Networks in several business processes. The organization of this paper is as follows. The first section gives a general introduction of Neural Networks. The second section highlights the business applications of neural networks. The third section dwells into the work done in the field of bankruptcy prediction followed by work in areas of credit card fraud detection. Section 5 talks about the work done in areas of Stock Market prediction which is followed by review of work in financial accounting. Finally we conclude this paper in section 6 followed by references and glossary.

1. General Introduction to Neural Networks

This section gives a general introduction of Neural Networks. Neural Networks imitates the working of human neuron and works on stimulus from outside world. Neural Networks using artificial intelligence are called Artificial Neural Networks or ANN [7]. An ANN consists of many single processors, which interact through a dense web of interconnections. A neuron or processing element has primarily two things to do. One is that it computes output, which is sent to the other PE's or outside the network. The neuron or PE determines its output value by applying a transfer function. Secondly, it updates a local memory, i.e. weights and other types of data called data variables. The neurons are organized into layers. The first layer is called the input layer and the last layer is the output layer. The inner layers, one or more, are known as hidden layers. The input neurons receive input values from outside the ANN's environment, whereas the output neurons send their output values there. A hidden or an output neuron receives input signals from the incoming connections and values from its local memory.

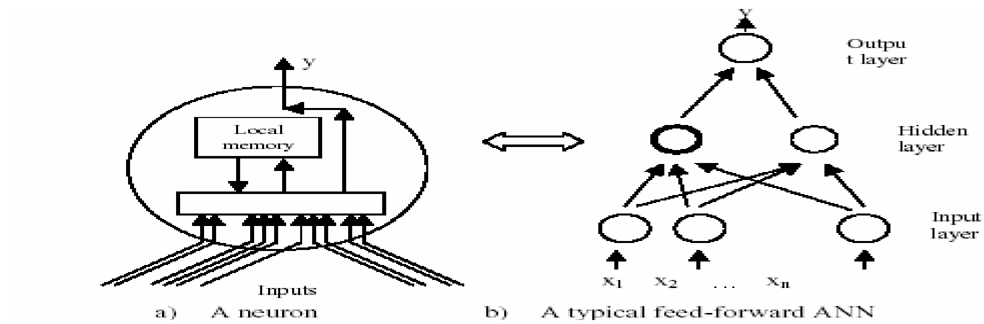
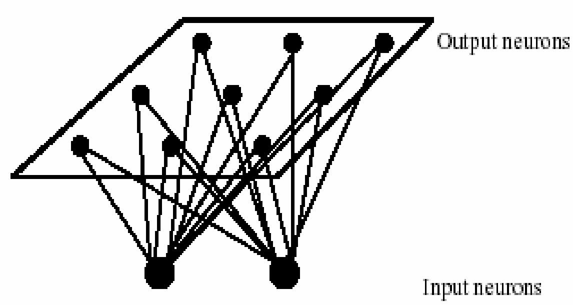


Figure 1: A Neuron and Artificial Neural Network

Various types of architectures are proposed for ANN in recent past. They are namely multi-layer perceptron, Kohonen's self-organising map (SOM) and Hopfield network [1, 2]. The first two are essentially feed forward networks because they feed the outputs to the neurons on the next layer while the latter is a feedback system.



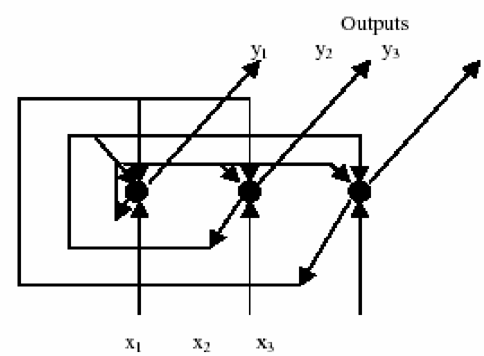


Figure 2: Kohonen's Self-Organizing Maps

Figure 3: Simple Hopfield Network

2. Business Applications of Artificial Neural Networks

Artificial Neural Networks or ANN has a multitude of real world applications in the business domain which have been classified as follows:

Accounting

- Identifying tax fraud
- Enhancing auditing by finding irregularities

Finance

- Signature and bank note verification
- Mortgage underwriting
- Foreign exchange rate forecasting
- Country risk rating
- Predicting stock initial public offerings
- Bankruptcy prediction
- Customer credit scoring
- Credit card approval and fraud detection
- Stock and commodity selection and trading

- Forecasting economic turning points
- Bond rating and trading
- Loan approvals
- Economic and financial forecasting
- Risk management

Human resources

- Predicting employee's performance and behavior
- Determining personnel resource requirements

Marketing

- Classification of consumer spending patterns
- New product analysis
- Identification of customer characteristics
- Sale forecasts
- Targeted marketing

The next four sections describes various ANN based solutions proposed for problems in fields of bankruptcy prediction, credit card fraud detection, stock prediction, and financial auditing respectively. We have reviewed the past 10 years work done in these 4 areas by studying various papers and journal articles as well as presentations that are available in public domain.

3. Applications of ANN in Bankruptcy Prediction

Bankruptcy prediction has long been an important and widely studied topic. The main impact of such research is in bank lending. Banks need to predict the possibility of default of a potential counter-party before they extend a loan. This can lead to sounder lending decisions, and therefore result in significant savings [10].
The forecast of bankruptcies belong to classification problems. With input variables, generally financial and accounting data on a firm, we try to find out in which category the firm enters, bankrupt or not bankrupt [11, 12]. The availability of a large amount of accounting and financial data on computerize databases, facilitates the use of artificial neural networks with quantitative data. They are tested as substitutes of traditional statistical tools such as multivariate discriminate analysis.
There are two main approaches to loan default/bankruptcy prediction. The first approach, the ***structural approach***, is based on modeling the underlying dynamics of interest rates and firm characteristics and deriving the default probability based on these dynamics. The second approach is the ***empirical*** or the ***statistical approach***. Instead of modeling the relationship of default with the characteristics of a firm, this relationship is learned from the data. In early empirical approaches, Altman used the classical multivariate discriminant analysis technique with following financial ratios as input variables:

1) Working capital/total assets
2) Retained earnings/total assets
3) Earnings before interest and taxes/total assets
4) Market capitalization/ total debt
5) Sales/total assets

These particular financial ratios have been widely used as inputs, even for NNs and other nonlinear models. Ohlson introduced the logistic regression approach (LR) to the bankruptcy prediction problem.

It is essentially a linear model with a sigmoid function at the output (it is thus similar to a single-neuron network). Because the output is in between 0 and 1, the model has a nice probabilistic interpretation. Ohlson used a novel set of financial ratios as inputs. Both the MDA model and the LR model have been widely used in practice and in many academic studies. They have been standard benchmarks for the loan default prediction problem.

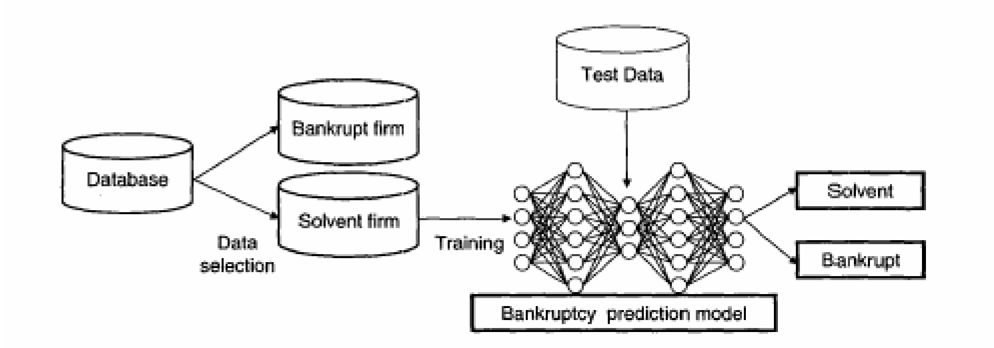


Figure 4: Bankruptcy prediction system framework

Research studies on using NN's for bankruptcy prediction started in 1990, and are still active now. Currently, several of the major commercial loan default prediction products are based on NN's. For example, Moody's *Public Firm Risk Model* is based on NN's as the main technology. Many banks have also developed and are using proprietary NN default prediction models.

Odom and Sharda [13] found that a back-propagation artificial neural network was superior to a Discriminant Analysis model in bankruptcy prediction of firms. In their survey of Savings and Loan Associations, Tam and Kiang [14] argue that empirical results have shown that ANNs have better predictive accuracy than Discriminant Analysis, Logit, k Nearest Neighbor (kNN) and Decision Tree (ID3) analysis.

From the many studies existing in the literature, it can be seen that NN's are generally more superior to other techniques. Also, the greatest part of the experimentations makes comparisons with traditional statistical forecast models such as ADM, Logistic Regression and Recursive Partitioning, but rare are the studies making a comparison between different neural networks. The ratios used for the implementations are never chosen specifically for a neural network application. The variables are extracted from traditional studies on bankruptcy forecast, or from the existing literature. The recognition of Artificial Neural Networks capacity in bankruptcy forecasting case appears through new experiments. With increasing research the ANN in not any more the object of comparison with traditional forecasting techniques, now it represents a tool of reference.

4. Application of ANN in Credit Card Fraud Detection

Fraud is increasing dramatically with the expansion of modern technology and the global superhighways of communication, resulting in the loss of billions of dollars worldwide each year. Although prevention technologies are the best way of reducing fraud, fraudsters are adaptive and, given time, will usually find ways to circumvent such measures. Methodologies for the detection of fraud are essential if we are to catch fraudsters once fraud prevention has failed. Statistics and machine learning provide effective technologies for fraud detection and have been applied successfully to detect activities such as credit card fraud.

One of the most interesting fields of prediction is the fraud of credit lines, especially credit card payments. For the high data traffic of 400,000 transactions per day, a reduction of 2.5% of fraud triggers a saving of one million dollars per year. The extent of credit card fraud is difficult to quantify, partly because companies are often loath to release fraud figures in case they frighten the spending public, and partly because the figures change (probably grow) over time. Various estimates have been given. For example, Leonard [19] suggested the cost of Visa/MasterCard fraud in Canada in 1989, 1990, and 1991 was 19, 29, and 46 million Canadian dollars, respectively. Ghosh and Reilly [20] suggest a figure of 850 million US dollars per year for all types of credit card fraud in the US, and Aleskerov *et al* [15] cite estimates of $700 million in the US each year for Visa/MasterCard, and $10 billion worldwide in 1996.

Credit card fraud may be perpetrated in various ways, including simple theft, application fraud, and counterfeit cards. Use of a stolen card is perhaps the most straightforward type of credit card fraud. In this case, the fraudster typically spends as much as possible in as short a space of time as possible, before the theft is detected and the card stopped, so that detecting the theft early can prevent large losses.

Application fraud arises when individuals obtain new credit cards from issuing companies using false personal information. Traditional credit scorecards (Hand and Henley [21]) are used to detect customers who are likely to default, and the reasons for this may include fraud. Such scorecards are based on the details given on the application forms, and perhaps also on other details, such as bureau information. Statistical models, which monitor behavior over time, can be used to detect cards, which have been obtained from a fraudulent application (e.g. a first time card holder who runs out and rapidly makes many purchases should arouse suspicion).

Cardholder-not-present fraud occurs when the transaction is made remotely, so that only the card's details are needed, and a manual signature and card imprint are not required at the time of purchase. Such transactions include telephone sales and online transactions, and this type of fraud accounts for a high proportion of losses. Researchers who have used neural networks for credit card fraud detection include Ghosh and Reilly [20], Aleskerov [15], Dorronsoro [18], and Brause [17], mainly in the context of supervised classification. HNC Software has developed ***Falcon***, a software package that relies heavily on neural network technology to detect credit card fraud.

Supervised methods, using samples from the fraudulent/non-fraudulent classes as the basis to construct classification rules detecting future cases of fraud, suffer from the problem of unbalanced class sizes mentioned above: the legitimate transactions generally far outnumber the fraudulent ones. Simple misclassification rate cannot be used as a performance measure: with a bad rate of 0.1%, simply classifying every transaction as legitimate will yield an error rate of only 0.001. Instead, one must either minimize an appropriate cost-weighted loss or fix some parameter (such as the number of cases one can afford to investigate in detail) and then try to maximize the number of fraudulent cases detected subject to this.

Further it can be seen that there is a dearth of published literature on fraud detection. Of that which has been published, much of it appears in the methodological data analytic literature, where the aim is to illustrate new data analytic tools by applying them to the detection of fraud, rather than being to describe methods of fraud detection per se. Furthermore, since anomaly detection methods are very context dependent, much of the published literature in the area concentrates on supervised classification methods. In particular, rule-based systems and neural networks have attracted interest.

5. Applications of ANN in Stock Market Prediction

Financial Market all over the globe is different from other sectors like HR etc. We could model any financial market as a complex feedback mechanism working on both external stimulus as well as past results. Prices are unstable and have a tendency to fall and rise by any magnitude. Typical example includes share markets all over the world. Stock Market involves trade risk; swap risk, and greater amount of uncertainty. Here the role of accurate prediction is highly appreciated for it was possible to predict it there would be no risk.

Neural networks have found ardent supporters among various avant-garde portfolio managers, investment banks and trading firms. Most of the major investment banks, such as Goldman Sachs and Morgan Stanley, have dedicated departments to the implementation of neural networks. Fidelity Investments has set up a mutual fund whose portfolio allocation is based solely on recommendations produced by an artificial neural network. The fact that major companies in the financial industry are investing resources in neural networks indicates that artificial neural networks may serve as an important method of forecasting.

In Stock Prediction, neural networks have been found useful in stock price prediction [4, 5]. Both Lee [4 have talked about using back propagation algorithm based Artificial Neural Networks for stock prediction. D. Pham [5] discusses various aspects of stock prediction processes and gives a general overview of it. Literature survey of last 5 years gives several solution models proposed for stock prediction problem. Some of the broader classification is Time Series method, recurrent neural network and Feed-forward neural network method [5]. These models are all used to learn the relationships between different technical and economical indices and the decision to buy or sell stocks. The inputs to the all the models are technical and economic indices. The output of the system is the decision to buy and sell and is mostly based on fuzzy logic where by system gives the decision not as a binary signal but as fuzzy signal with a certain percentage of success.

Peifer [7] advocated deploying an AI based Neural network for stock prediction. This system should use sufficient amount of historical stock data as input and then train the network with this data. Once trained the neural network can be used to predict stock behavior [7]. Most of the papers we have studied in this area, advocated use of Backpropagation algorithm [6] in ANN for stock prediction. Maijana Zekic has done a detailed analysis of Neural Network Applications in Stock Market Predictions as part of their MS thesis [8].

Analysis of the problem domains of NN applications has shown that there are three main groups of problems that NN applications frequently deal with. First group consists of predicting stock performance by trying to classify stocks into the classes such as: stocks with either positive or negative returns and stocks that perform well, neutrally, or poorly. Such NN applications give valuable support to making investment decisions, but do not specify the amount of expected price and expected profit. The next group of frequently used applications gives more information: NN's for stock price predictions. Such systems try to predict stock prices for one or more days in advance, based on previous stock prices and on related financial ratios. The third important group of NN applications in stock markets is concerned with modeling stock performance and forecasting.

An important trend in the applications is combining two or more NN's into a single NN system, or incorporating other artificial intelligence methods into a NN system, such as expert systems, genetic algorithms, natural language processing. The number of Kohonen's, Hopfield's, and other algorithms is relatively small in the stock market NN applications. Following table summarizes use of various solutions provided in Stock prediction market.

S	Problem Domain	Solutions given
1	Predicting stock performance	Backpropagation Boltzman machine
2	Stock price predictions	Backpropagation Perceptron, ADALINE /MADALINE
3	Modeling the stock performance (ANN combined	Backpropagation Hybrid approach (Backpropagation NN + Expert system)

Table 1: Solutions provided in Stock prediction market

After a brief overview of the articles and papers, it was evident that almost all applications of NN in stock markets are based on a different data model. The authors emphasize the necessity for including more data in the models, such as other types of asset; more financial ratios; and qualitative data. Furthermore, the recommendation for the use of various time periods occurs frequently. Stocks are commonly predicted on the basis of daily data, although some researchers use weekly and monthly data. Additionally, future research should focus on the examinations of other types of networks that were rarely applied, such as Hopfield's, Kohonen's, etc. Finally, almost all researchers emphasize the integration of NN's with other methods of artificial intelligence as one of the best solutions for improving the limitations.

Marijana [8] in her paper says that Back propagation algorithm has the ability to predict with greater accuracy than other NN algorithms, no matter which data model was used. She also says that NN outperform classical forecasting and statistical methods, such as multiple regression analysis and discriminate analysis. The combination of the NN calculating ability based on heuristics and the ability of expert systems to process the rules for making a decision and to explain the results can be a very effective intelligent support in various problem domains [1, 3, 5].
After completing several simulations for predicting several stocks based on the past historical data using fuzzy neural network with the Back-Propagation learning algorithm, it is conclusive that the average error for simulations using lots of data is smaller than that using less amount of data. That is, the more data for training the neural network, the better prediction it gives. Further, it can be concluded that:

1. NN's are efficiency methods in the area of stock market predictions, but there is no "recipe" that matches certain methodologies with certain problems.

2. NN's are most implemented in forecasting stock prices and returns, although stock modeling is very promising problem domain of its application.
3. Most frequent methodology in ANN's is the Back propagation algorithm, but many authors emphasize the importance of integration of NN with other artificial intelligence methods.
4. Benefits of NN are in their ability to predict accurately even in situations with uncertain data, and the possible combinations with other methods.
5. Limitations have to do with insufficient reliability tests, data design, and the inability to identify the optimal topology for a certain problem domain.

6. Applications of ANN in Financial Auditing

Our study of ANN in the financial domain is how information technology developments affect the nature of the audit process and the audit skills. In this section we have reviewed several papers and articles and the review showed that the main application areas in auditing were material errors, management fraud, and support for backing concern decision. ANN's have also been find huge applications in control risk assessment, audit fee, and financial distress problems.

Very many things in our business and auditing environment are changing at an increasing rate. Increased competition and the need for faster and better information for decisions mark today's business environment. In addition, systems are complex and many times on-line. This complexity means that auditors have more and different kinds of work to do than they had earlier. In case of Indian financial sector, in early 90's most of the work is done by pen and paper way i.e. is use of electronic means is pretty less. But now things are changed. All major Audit firms like PWC [9], Vaish Associates, Kothari and Kothari etc. have all gone electronic in process. Following table summarizes different levels of software tools used by a modern auditor today.

STAGE	SOFTWARE APPLICATION	UTILIZATION
I	word-processing, spreadsheets	Documentation, auditor's report, financial analysis and calculations
II	graphics, external databases, electronic mail	Audit planning, comparison of financial information, company analysis
III	company models, audit databases, IS audit software applications	Testing of information systems, database inquires
IV	expert systems, decision support systems, special software for continuous audit	Expert analysis for finding important tasks for audit
V	Advanced method, ANN-based systems	Assurance services

The major ANN-application area in auditing is material errors. Material error applications direct auditors' attention to those financial account values where the actual relationships are not consistent with the expected relationships. An auditor has to decide whether and what kind of further audit investigation is required to explain the unexpected results. Auditors cannot assume that the management is honest or dishonest for most of the records here are fraudulent. Management fraud (MF) can be defined as deliberate fraud committed by the management that injures investors and creditors through materially misleading financial statements.

An auditor considers a huge amount of data when assessing the risk of the internal control (IC) structure of an entity failing to prevent or detect significant misstatements in financial statements. Curry and Peel [16] provided an overview of the ANN modeling approach and the performance of ANN's, relative to conventional ordinary least squares (OLS) regression analysis, in predicting the cross-sectional variation in corporate audit fees (AF). As information technological changes occur at an increasing rate, auditors must keep pace with these emerging changes and their impact on their client's information processing systems as well as on their own audit procedures. This study pictures the current state of the ANN-applications connected to auditing purpose. The review is comprehensive but by no means exhaustive, given the fast growing nature of the literature.

In brief, the main findings are summarized as follows: The main application areas were material errors, management fraud, and support for going concern decision. ANN's have also been applied to internal control risk assessment, audit fee, and financial distress problems.

7. Conclusions

Artificial Neural Networks offer qualitative methods for business and economic systems that traditional quantitative tools in statistics and econometrics cannot quantify due to the complexity in translating the systems into precise mathematical functions. Hence, the use of neural networks in finance is a promising field of research especially given the ready availability of large mass of data sets and the reported ability of neural networks to detect and assimilate relationships between a large numbers of variables.

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Glossary

ANN	: Artificial Neural Networks
AI	: Artificial Intelligence
BA	: Backpropogation algorithm
NN	: Neural Networks
DSS	: Decision Support Systems
NN	: Neural Networks