Knowledge Based Descriptive Neural Networks

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Abstract This paper presents a study of knowledge based descriptive neural networks (DNN). DNN is a neural network that incorporates rules extracted from trained neural networks. One of the major drawbacks of neural network models is that they could not explain what they have done. Extracting rules from trained neural networks is one of the solutions. However, how to effectively use extracted rules has been paid little attention. This paper addresses issues of effective ways of using these extracted rules. With the introduction of DNN, we not only keep the good feature of nonlinearity in neural networks but also have explanation of underlying reasoning mechanisms, for instance, how prediction is made.

1. INTRODUCTION

Artificial neural networks are computer software that emulates biological neural networks. A neural network model is a learning system made up of simple units configured in a highly interconnected network. Neural networks are normally classified as one of soft computing techniques. Soft computing is a collection of techniques spanning many fields that fall under various categories in computational intelligence. Soft computing methodologies including neural networks, genetic algorithms, granular computing, fuzzy sets, rough sets and wavelet are widely applied in data mining and knowledge discovery process [8].

Recently, a granular computing model for knowledge discovery and data mining is proposed by combining results from formal concept analysis and granular computing [18]. The essence of soft computing is that unlike the traditional, hard computing approach, it is aimed at an accommodation with the pervasive imprecision of the real world. The guiding principle of soft computing is:

> "*exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution cost, and better rapport with reality*" [19].

Knowledge discovery in databases or KDD has been defined as the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data. Data mining as one of the processes in KDD is the application of data analysis and discovery algorithms that under acceptable computational efficiency limitations produce a particular enumeration of patterns over the data. However, researchers do not differentiate these two terms. Generally speaking, there are two types of data mining approaches, namely descriptive data mining and predictive data mining. Descriptive data mining explores interesting patterns to describe the data while predictive data mining forecasts the behavior of the model based on available data set. Due the black box nature of neural networks, they sometimes are not classified as data mining tools for discover interesting and understandable data mining definition. Information or knowledge embedded in trained neural networks is hard to be verified or interpreted by human beings.

There are two conventional types of forecasting models, namely qualitative and quantitative approaches. Qualitative methods are incapable to separate individual's biases from objective facts. Quantitative approaches are weak in applications with nonlinearity in the data set. Artificial neural networks can learn from examples and exhibit some capability for generalization, beyond the training data. Indeed, they have been used in such diverse applications as handwriting recognition, medical diagnosis, exchange rate prediction, stock market assessment and prediction, and many more. For instance, they have been shown [11, 16] to outperform traditional forecasting models in relation to numerous business classification and prediction problems. In addition, neural networks have been shown mathematically to be universal approximators of functions and their derivatives [15]. Hence the potential benefits to various applications may be unlimited.

Taking financial forecasting as an example, there are two major problems in the use of neural networks. One is that the underlying structural factors are not static and thus there is pressure to find the trends quickly while they are valid, as well as to recognize the time when the trends are no longer effective. The second problem is that, while neural networks have proved to be far more effective at forecasting than more conventional linear techniques like regression analysis, their decision processes are not easily understandable in terms of rules that human experts can verify. Businesses are reluctant to invest in forecasting techniques, however effective, if there is not a clearly understandable causal base to the model. In other words, these neural networks operate as “black boxes”. In many applications, it is desirable to extract knowledge from trained neural networks for users to gain better understanding of the problem at hand [12]. If the prediction performed by a neural network could be understood and explained, then there would be much more widespread acceptance of this technology. This would then pave the way for even more applications of this powerful technology.

This paper addresses the issues of usage the discovered underlying rules by neural networks. It presents an ongoing project of incorporating rules extracted from trained neural networks to form a knowledge based descriptive neural network--DNN. The organization of this article is as follows. The next section gives a brief review of techniques of rules extraction from neural networks. A section discusses the construction of the descriptive neural networks is followed. Finally, a conclusion section ends with this paper.

2. Rules Extraction From Trained Neural Networks

Neural networks achieve high accuracy in classification, prediction and many other applications as suggested in the literature. As mentioned above, being unable to explain the knowledge embedded in trained neural networks is one of the major drawbacks of this technology. Much of attention has been paid to solve this problem by extracting rules from trained neural networks.

According to the taxonomy of Tickle *et al.* [14], neural network rule extraction techniques may be classified into five dimensions, namely, (1) the "expressive power" of the extracted rules (format or type of rules extracted); (2) the "quality" (accuracy, fidelity, consistency and comprehensibility) of the extracted rules; (3) the "translucency" of the view taken within the rule extraction technique of the underlying network units (i.e. using of decompositional or pedagogical); (4) the complexity of the algorithms; (5) the portability to network architectures and training regimes. A sixth dimension, the treatment of linguistic (i.e., binary, discretized and continuous) variables has been considered by Duch *et al.* [4].

Many researchers have been working on extracting rules from trained networks, as reasoning with logical rules is more acceptable to users than black box systems [1]. Setiono's work [12] is one of the examples to address this problem and open the black box of neural networks. Andrews *et al.* [1] classified techniques of extraction of symbolic logical rules from neural network into two groups. The rules are extracted at the level of individual hidden and output layer units by decomositional approach [13]. With pedagogical approach [1, 12], the network is treated as a 'black box'; extracted rules describe global relationships between inputs and outputs; no analysis of the detailed characteristics of the neural network itself is undertaken.

The fifth criterion of taxonomy of Tickle *et al.* [14] is to measure the generalization ability of the technique. This dimension can be extended to applications as well. For instance, in the area of financial forecasting with neural networks the rules should be as simple as possible from practitioner's point of view. In fact, although there are dozens of technical indicators available, most of traders only stick on a couple of indicators. A trader may only look at 10 day and 30 day moving average. The rules he used might be "When the 10 day moving average crosses above the 30 day moving average and both moving averages are in an upward direction it is the time to buy" and "When the 10 day moving average crosses below the 30 day moving average and both moving averages are directed downward it is time to sell." If the inputs of a neural network include 10 day and 20 day moving averages and the output is buy or sell, similar rules may be extracted from the trained neural networks. However, neural networks are more complex than this one in most cases therefore the rules are more complex than the cited examples. In any case, the rules extracted from neural networks should be easily interpreted and transferred into actions by traders. If we only use these discovered rules, we only treat neural networks as one of data mining tools. As suggested by many researchers that neural network technique is one of the best forecasting candidates of financial forecasting, we would better use neural networks as forecasting tool instead of just use the discovered forecasting rules from trained networks. This research is trying to incorporate discovered rules into neural network models.

3. Construction of Descriptive Neural Networks

Following the above discussion, we will present our proposed novel descriptive neural network -- DNN in this section. The DNN is a neural network embedded with business rules that have been discovered from previously trained networks. The architecture of DNN is not only decided by training examples but also by hidden rules extracted from trained networks. One of the aim of our descriptive technique is to create and use innovative a second layer of rule extraction techniques to explicate the hidden rules from previously trained neural networks. This will enable us to explain the mechanism of a neural network forecasting model.

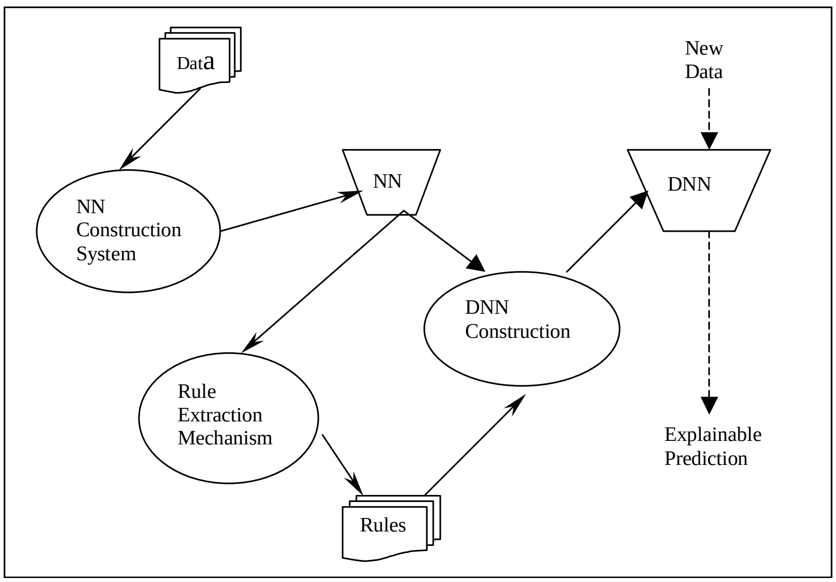

Figure 1 Procedures of DNN Construction

An additional aim is to be able to extract the factors that actually drive business decision-making for instance. The DNN system to traditional neural network is similar to econometrics to regression analysis. One of advantages of neural networks applied in the forecasting domain is that high forecasting accuracy may be achieved without knowing domain knowledge. Armstrong [2] stated in his principle 10.2 that “let the data speak for themselves” is ill -suited for forecasting. It may not acceptable by practitioners if only regression or neural network models are used as forecasting tools. Econometrics is the technique using statistical analysis combined with economic theory to analyze economic data. It presents more economic knowledge than a single mathematical formula and thus more popular and acceptable to practitioners. In fact, it is more accurate than regression models.

There are three steps involved in the construction of the proposed DNN networks as depicted in Figure 1. The first step is to build neural network forecasting model by the neural network construction system [17]. The mechanism of the subsystem is like an Expert System Shell. It assists users to build a forecasting model by analysis available data and some domain knowledge. The neural network construction system contains all manual procedure components involved in construction of neural networks such as data preprocessing, input/output selection, sensitivity analysis, data organization, model construction, post analysis and model recommendation. It will decide the neural network forecasting models used in a particular financial application domain; perform the tedious trial-and-error training procedures; and relieve the human from most of the analysis jobs.

The system also contains a knowledge base that enables an inexperienced user to construct a neural network forecasting model without worry about techniques details such as trading strategies, data sampling, and data partitioning. Self-adapting facilities are included in the model construction system. Time series and its related fundamental series (if any) are fed to the system when used in developing financial forecasting models for instance. Different market information will then be analyzed by the system to automatically determine the model parameters, network size, data frequency, etc. Statistical and R/S analyses are also conducted by the system to gauge the behavior of markets. To minimize recency problem, some technical indicators, such as smoothing indicators will also be derived from the original time series.

There is an Existing Knowledge Base that initially stores the information of human experience from manual training procedures. The system will then proceed to collect all the related information through its own experiences, as it keeps track of the performance of each model. After a forecasting model is constructed, the system will analyze and generalize the information in a new knowledge base called Current Record. The Existing Knowledge Base will be updated according to the new knowledge extracted from current construction. The knowledge base contains two parts in representing two kinds of knowledge, namely, general knowledge and case specific knowledge. A piece of specific knowledge is stored as it is. It just states a fact in which kind of situation how much profit was gained. This kind of information is recorded in Current and will be converted to Existing Knowledge Base.

The second step is to extract rules from trained the neural networks. Neural network architecture and weight space are used to mine the business rules that govern the forecasting by the rule extraction mechanism. Many rule extraction techniques such as decompositional and pedagogical, Boolean rule have appeared in the literature [5, 12 & 13]. We are particular interested in the business rules could be applied to financial forecasting in our preliminary study as little research has been done in this area. We need further study on the specific features of rule extraction for financial forecasting models. If we can explicate the hidden forecasting rules from previously trained neural networks, we thus will be able explain the mechanism of a neural network forecasting model.

In the third step hidden forecasting rules extracted in the previous step are incorporated to the network generated by neural network construction system to form a descriptive neural network, DNN. Most of researchers extract if-then type association rules, as they are more understandable for humans than other representations [4]. The rules created from neural networks can then be converted in decision tree or used in other expert systems. The uses of rules here have limited neural network' s ability to model nonlinear data especially in financial applications. DNN is an artificial neural network with descriptions of the domain knowledge of applied area. So that not only predictions can be made but also the reasons for the predictions can be explained. DNN to conventional neural networks is like econometrics to regression. It incorporates uncovered rules such as propositional rules [3, 9] and fuzzy rules [5] as well as domain knowledge to traditional neural networks. We expect that DNN networks could make more accurate and explainable predictions. Some issues in construction of DNN include knowledge based management, architecture enhancement, rule measurement criteria, threshold adjustment, fuzzy representation, etc.

Fuzzy neural networks can be considered as the simplest DNN. Neural network ensemble can be considered as the second type of DNN. A neural-network ensemble a set of separately trained neural networks that are combined to form one unified prediction model [10]. Each trained neural network in the collection of ensemble can serve a different rule in modeling. Suppose we use three neural networks in financial forecasting. They are used to forecast different movements such as primary trend, secondary movements and day fluctuations as in Dow Jones theory. These networks are served as committee members [17] in the forecasting and decision making processes. A more complex DNN is to incorporate rules extracted from the previous step. The rules are used in construction of neural networks in terms of the architecture and weights. The weighs to or from the most influence factors are set the highest in the retraining. Some unimportant factors could be passed. For instance, if we find that the daily movement has the least influence to long term forecasting, we could eliminate the node or the neural network that are severed as daily movement component.

4. Concluding Remarks

Data mining covers most of soft computing techniques. Neural networks are widely used in applications such as forecasting, pattern recognition, and classification. Although research has shown that neural networks are more effective and accurate in many areas than traditional statistical models for instance, industry people are reluctant to invest in such a good technology due to the lack of explanation of its mechanism of modeling. Extracting rules from trained neural networks is one of the solutions to this problem. However, just use the rules extracted from neural network does not take full advantages of neural network. This paper addresses the issues of using discovered rules in a way to incorporate them to neural networks. It presents a descriptive neural network model, i.e. DNN that is expected to make more accurate and explainable forecasts. Further research on this topic includes theoretical extension and enhancement of the techniques by integration with other softcomputing techniques such as fuzzy logic, rough sets, and genetics algorithms; refining techniques of DNN construction and rules extraction; Further investigation the rules extracted in order to make full advantages from them.

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