Towards a Better Forecasting Model for Economic Indices

Jing Tao YAO
Department of Computer Science
University of Regina
Regina, Saskachewan
Canada S4S 0A2
Email: yaojt@acm.org

Abstract

This paper presents a study of neural network forecasting construction system. Forecasting, especially financial forecasting has been attracting researchers and practitioners for many years. Many experiments suggest that neural networks can outperform conventional models in most cases. However, due to the tedious and time consuming of neural networks training, some of models reported in literature did not go through comprehensive experiments. We propose a neural network forecasting construction system based on the study of manual training procedures. We hope that the system will free human beings from the tedious trial-and-error procedures and thus more progress can be achieved for neural networks in financial applications.

Introduction

Knowing future better has attracted many people for thousands of years. The forecasting methods vary greatly and will depend on the data availability, the quality of models available, and the kinds of assumptions made, amongst other things. Generally speaking, forecasting is not an easy task and therefore it has attracted many researchers to explore it. The finance problems are very complex and different with different cases. They are influenced by not only economic related factors but also other factors such as politics, human action and even psychological. However, due to the profit concerns and other considerations, much of the useful information is not available to the public. The changes of financial markets are very fast, even the tick-tac data is available nowadays. The changing speed is very fast and makes the forecasting even more difficult. However, there should be rules for the development and application in theory that can be discovered. This is similar to a war, although it is difficult to say which side will win, the smart leaders will always lead his army to the victory. This shows that it is still possible to get a good result if we analyse in depth, are on the right track and use the right approaches.

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. Many researchers [7] have suggested that neural networks can serve as alternative and novel tools in business, e.g., in forecasting financial time series.

Neural network based financial forecasting has been explored for about a decade. Many research papers are published in various international journals and conferences. Some companies and institutions are also claiming or marketing the so-called advanced forecasting tools or models. Some people even think that neural network is a panacea. Merely getting a better or more accurate forecasting is not too tough a job for researchers and practitioners nowadays. The application in financial domain however makes only slow progress as the practitioners are not willing to release their commercial secrets.

Instead of just presenting one successful experiment, possibility or confidence level can be applied to the outputs. Data are partitioned into several sets to find out the particular knowledge of this time series. As stated by David Wolpert and William Macready about their No-Free-Lunch Theorem [6], averaged over all problems, all search algorithms perform equally. Although they are talking about genetic algorithms for optimization, it may be true for neural network forecasting. Just experimenting on a single data set, a neural network model that outperforms other models can be found. However, for another data set one model that outperforms neural network model could also be found according to No-Free-Lunch Theorem. To avoid such a case of one model outperforming others, researchers partition the data set into several sub data sets and use boot strapping or windowzing techniques in order to get a model that works for all sub data sets. The recommended neural network models are those that outperform other models for all sub time horizons. In other words, only those models incorporated with enough local knowledge can be used for future forecasting. However, the training of neural networks are time consuming and tedious and thus some researchers are not willing to test more on their data set. Cohen [1] surveyed 150 papers in the proceedings of the 8th National Conference on artificial intelligence (1990). He discovered that only 42% of the papers reported that a program had run on more than one example; just 30% demonstrated performance in some way; a mere 21% framed hypotheses or made predictions. He then concluded that the methodologies used were incomplete with respect to the goals of designing and analyzing AI system.

Tichy [4] showed that in a very large study of over 400 research articles in computer science. Over 40% of the articles are about new designs and the models completely lack experimental data. He also points out 16 excuses to avoid experimentation for computer scientists [5]. What he is talking is true and not a joke. Prechelt [3] showed that the situation is not better in the neural network literature. Out of 190 papers published in well-known journals dedicated to neural networks, 29% did not employ even a single realistic or real learning problem. Only 8% of the articles presented results for more than one problem using real world data.

All these indicate that we need sufficient experiments to build a neural network forecasting model. To test only for one market or just for one particular time period means nothing. Based on manually, trial-and-error, or ad hoc experiments will not lead to a robust model. If there is a system that can help us to formalize these tedious exploratory procedures, it will certainly be of great value to financial forecasting. We will present a study on the neural network forecasting construction system in this paper. First we will brief steps of neural network forecasting in the next section. A section that discuses the construction system is followed. Finally, we conclude this paper in the last section.

The Art of NN Training

The neural network training is an art. Many searchers and practitioners have worked in the field to work towards successful prediction and classification. A seven-step approach for NN financial forecasting model building is adopted here. The seven steps are basic components of the automated system, as we will discuss in the next section, and normally involved in the manual approach. Each step deals with an important issue. They are data preprocessing, input and output selection, sensitive analysis, data organization, model construction, post analysis and model recommendation [9]. Figure 1 shows the steps of a neural network forecasting model construction steps.

More robust model is needed but not only in one market or for one time period. Because of the lack of industrial models and because failures in academic research are not published, a single person or even a group of researchers will not gain enough information or experiences to build a good forecasting model. It is obvious that an automated system dealing with neural network models building is necessary. In the next section we will discuss all the steps and integrate them into one system.

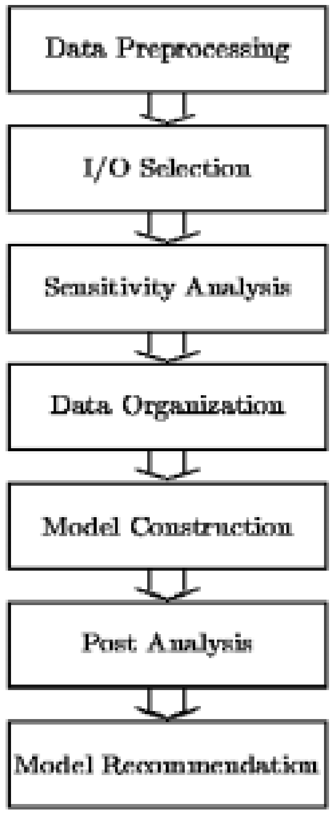

Figure 1 Neural network forecasting model building steps

Neural Network Forecasting Model Construction System

The normal steps of modeling financial data are quite tedious. We need to experiment, analyze, and test. Based on our experience in manual model construction, we propose a neural network forecasting model construction system. The system will decide the NN forecasting models used in financial application domain, perform the tedious trial-and-error procedures and relieve the human from most of the analysis jobs. This system will let the users feed the whole data to the system, after analyzing data, the output will provide a (group of) NN model(s) including parameters, time, frequency, and other factors. Once the new data are available, one can just feed it to the NN model, and prediction could be made. The system is depicted in Figure 2.

The components of the system are mainly the steps that shown in Figure 1. Data is prepared for use in *Data Preprocessing*. Derived indicators, noises and missing data are processed too. *Selection of I/O*: select suitable inputs and outputs based on the

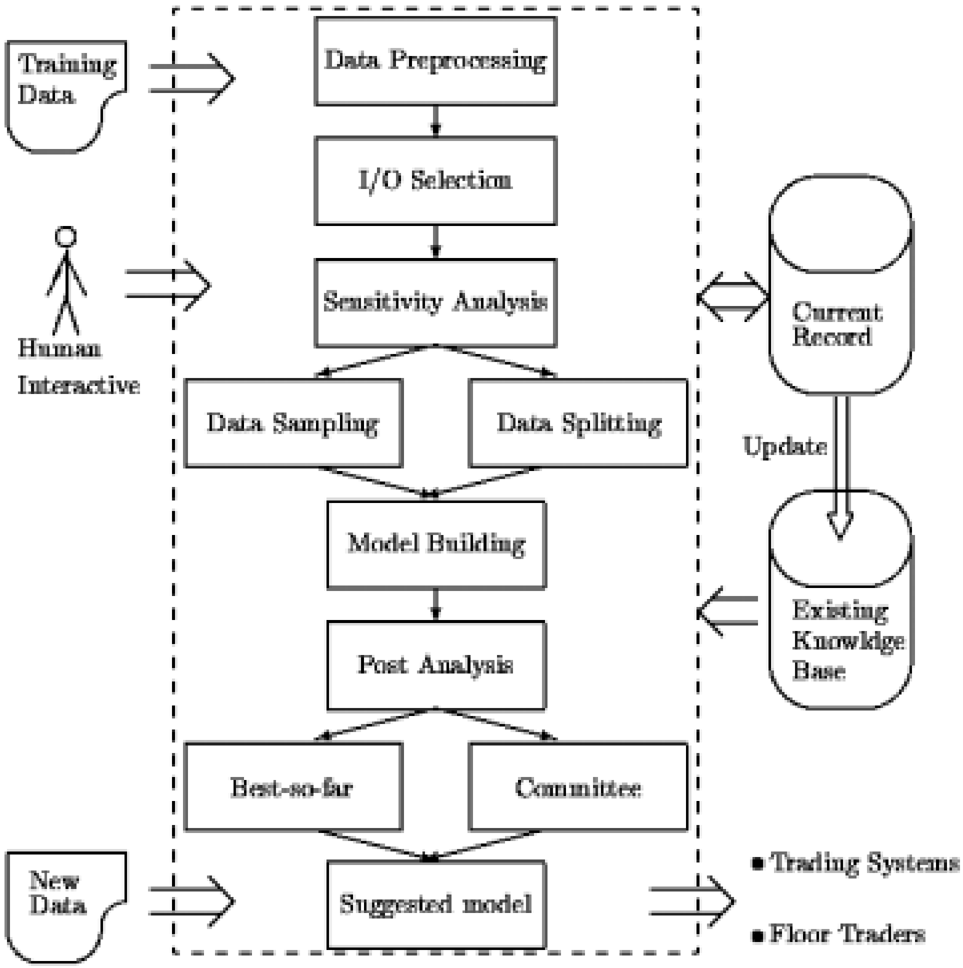

Figure 2 A pictorial depiction of the model construction system

the requirements and available information. *Sensitivity Analysis* is used to find out which input is more sensitive to the outputs. In other words, after a sensitivity analysis, we can eliminate the less sensitive variables from the input set to make the network simple and effective. The next step is *Data Organization*. We have chosen the prediction goal and the inputs that should be used. However, we need to sample and/or split data into subsets so that we can efficiently use available data. The historical data may not necessarily contribute equally to the model building. We can emphasize a certain period of data by feeding more times to the network or eliminate some data pattern from unimportant time periods. *Model Construction* step deals with neural network

```
if (number_of_data < minimum_data)
  then       not_recommended_for_training

  if (number_of_data > splitting_threshold)
  then       split_data_into_subset

 if (splitting)
 then    set first training_percent as training_set
              set next validation_percent as validation_set
              set remaining testing_percent as testing_set

  if (x[i-j] > x[i] > x[i+j])
  then
     trend[i][j] := up_trend

  if (x[i-j] <= x[i] <= x[i+j])
     trend[i][j] := down_trend

  if (x[i-j] <= x[i] > x[i+j])
  then
     trend[i][j] := peak_trend

  if (x[i-j] > x[i] <= x[i+j])
     trend[i][j] := valley_trend
```

Figure 3. Some of the rules in the Existing Knowledge Base

architecture, hidden layers and activation function. With only one case of success does not mean it will be successes in the future. In our approach, we do not just train the network once using one data set. The final neural network model we suggested in using of forecasting is not a single network but a group of networks. The networks are amongst the best model we have found using the same data set but different samples, segments, and architectures. The *Model Recommendation* could be either Best-so-far or Committee. Best-so-far is the best model for the testing data and in the hope of that it is also the best model for the future new data. As we cannot guarantee that the only one model is suitable for the future, we recommend a group of models as a committee in our final model. When forecast is made, instead of basing on one model, it can conclude from the majority of the committee. As on the average, the committee suggestion for the historical data is superior to a single model. Therefore the possibility for future correctness is greater.

A self-adapting facility is included in the model construction system. Time series and its related fundamental series (if any) are fed to the system. 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 [2] are also conducted by the system to gauge the behavior of markets. All the information will be stored in an Existing Knowledge Base. To minimize recency problem, some technical indicators, such as smoothing indicators will also be derived from the original time series.

The system also gives the frequency support. It determines the sampling frequency according to the dynamic analysis of real data rather than basing on the assumption. Whether we should sample more for which kind of period is dependent on the experiment of this particular data set is depending on the data. The system conducts forecasting on historical data based on different sampling rules. It is to be noted that we only sample on the training or validation data, the testing set will remain the same so that after the model is built we need not sample the new data and feed it to the model. Moving windows will be applied for the whole data set. Profit gaining is the main goal for our system. Although the criterion of stopping training can still be the traditional least squared errors, we will use profit as a measure for the testing. This means that only the profit is considered over and above the minimized squared errors. The models that are selected based on the least squared error will be the candidates for profit criterion. In addition, using Directional Profit Model or Time Dependent Directional Profit Model [8] will be easier as they consider the profit at the time of training.

The Existing Knowledge Base initially stores the information of our 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 Current Record. The Existing Knowledge Base will be updated according to the new knowledge extracted from current construction. Besides model architecture and data segment, other factors such as trading strategies, trading rules, and risk management are recorded and referenced in the knowledge base. 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 Record and will be converted to Existing Knowledge Base. According to specific examples, general knowledge will be formed in a format such as *if . then.* For instance, some of the rules in the Existing Knowledge Base are shown in Figure 3.

Concluding Remarks

Neural networks are suitable for financial forecasting and marketing analysis. They can be used for financial time series, such as stock exchange indices, foreign exchange rates, forecasting. They can also be used in marketing such as retail sales analysis and forecasting and advertisement allocation. Some people treat neural network as a panacea. However, there is no cure-all medicine in the world. When applying a neural network model in a real application, attention should be taken in every single step. The usage and training of a neural network is an art. One successful experiment says nothing for real application. Segmenting data into several sub sets and training with a neural network with the same architecture will assure that the model will not just work for a single data set. Furthermore, building a model construction system will free human beings from the tedious trial-and-error procedures. Setting up a model building system is the first step towards a better forecasting model. The automation of neural network training together other techniques will lead us to a new horizon for using neural network model as a financial times series forecasting tool.

Reference:

[1] Cohen, Paul R., “A Survey of the Eighth National Conference on Artificial Intelligence: Pulling Together or Pulling Apart? ”, *AI Magazine*, Vol. 12, No. 1, 1991, pp17-41.

[2] Peters, E. E., *Chaos and Order in the Capital Markets*, John Wiley & Sons, 1996.

[3] Prechelt, L, “A Quantitative Study of Experimental Evaluations of Neural Network Learning Algorithms: Current Research Practice”, *Neural Networks*, Vol. 9. No. 3, 1996, pp457-462.

[4] Tichy, W. F., P. Lukowicz, L. Prechelt and E. A. Heinz, “Experimental Evaluation in Computer Science: A Quantitative Study”, *Journal of Systems and Software*, Vol. 28, No. 1, 1995, pp9-18.

[5]Tichy, W. F., “Should Computer Scientists Experiment More? 16 Reasons to Avoid Experimentation”, *IEEE Computer* Vol. 31, No. 5, 1998, pp32-44.

[6] Wolpert, D.H., W.G. Macready, “No Free Lunch Theorems for Search”, *Technical Report of The Santa Fe Institute*, SFI-TR-95-02-010, 1996.

[7] Wong, B. K, T A Bodnovich, Y Selvi, “Neural Network Applications in Business: a Review and Analysis of the Literature (1988-1995) ”, *Decision Support Systems*, Vol 19, No. 4, 1998, pp301-320.

[8] Yao, J.T., C.L. Tan, “Time dependent Directional Profit Model for Financial Time Series Forecasting”, *Proceedings of The IEEE-INNS-ENNS International Joint Conference on Neural Networks*, Como, Italy, 24-27 July 2000, Volume V, pp291-296.

[9] Yao, J.T., C. L. Tan, “Guidelines for Financial Forecasting with Neural Networks”, *Proceedings of International Conference on Neural Information Processing*, Shanghai, China, 14-18 November, 2001.