Stock Market Forecasting Using Artificial Neural Networks

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Abstract

Many papers on forecasting the stock market have been written by the academia. In addition to that, stock market prediction is an everyday concern for many professionals in the finance industry. The possibility of achieving real returns with the help of scientific methods explains the interest in the field. The spectrum of econometric tools applied to this problem has been a considerably large one. In addition to the papers written using those tools, application of artificial neural network methods has been a profilerating area in the last ten years. Success of the hedge funds applying quantitative trading and asset management strategies has especially been an important motivation for research. This paper examines the ability of artificial neural network models in forecasting the Istanbul Stock Exchange stock index hence the applicability of a quantitative strategy in the Turkish financial market.

Keywords: Stock market forecasting, artificial neural networks

1) Introduction

Artificial intelligence has a wide range of application areas although it is a relatively new discipline. As a popular subtopic of artificial intelligence, artificial neural networks have been subject to research in such diverse areas as aerospace, telecommunications, transportation, medication and entertainment. The proliferation of research on artificial neural networks is partly due to the real world applicability of the models.

In the last two decades, financial applications of artificial neural networks have also emerged. Prediction of stock markets have been among the topics, such as forecasting of financial failures and evaluation of credits, examined. Multilayer feedforward backpropagation networks are mostly used among other artificial neural network models for financial forecasting.

Forecasting the stock market is both an interesting challenge for academics and an ultimate goal for many finance professionals. There has been a great deal of controversy on whether the financial markets behave randomly or non-randomly among finance academics. Bulton Malkiel (1991) from Princeton argues in his book, A Random Walk Down the Wall Street, that it is not possible to constantly beat the stock market due to the random behaviour of asset prices. On the other hand, Andrew W. Lo and A. Craig MacKinlay (2001) from MIT contradict the random walk hypothesis, thus the efficient market hypothesis, in their book, A Non-Random Walk Down the Wall Street, with the simple volatility-based specification test.

Application of mathematical models such as artificial intelligence tools have been subject to great interest due to the success of the quantitative investment funds in the last years. Especially quantitative hedge funds, employing many distinguished academics in quantitative fields, have popularized the use of mathematical and statistical tools in trading with their extremely high returns and ability to beat the market in consecutive years*.

The aim of this paper is to build an artificial neural network model to forecast the return of the ISE-100 stock index by using financial market data that are believed to be most commonly followed by the asset managers in the Turkish asset management industry as inputs of the model. By doing so, it is intended to examine whether it is possible to forecast the return of the stock index accurately enough to make use of analytical models in the decision making process of investments.

*Renaissance Technologies, D.E. Shaw are examples of such quantitative hedge funds.

2) Literature Review

Özer and Ertokatlı (2010) argue that the ISE market index is not behaving randomly. The test results indicate that the ISE returns are chaotic and not linear. The efficient market hypothesis is rejected for the ISE.

Egeli, Özturan and Badur (2003) aim to find the best model to predict the Istanbul stock exchange. They use multilayer perceptron and generalized feed forward network architectures with 1,2 and 4 hidden layers and also 5-day and 10-day moving average models. The prediction results of the eight models are compared using coefficients of determination and mean relative percentage errors. It is concluded that the predictions based on the artificial neural network models are more accurate than the moving average models and the generalized feed forward architecture is more suitable for prediction.

Avcı (2007) forecasts the ISE-100 index using a three layer multilayer perceptron model with lagged values of the index and volume as inputs. The findings of the study are that the neural network performance is time dependent and the input selection is an important determinant of the network performance. Avcı used the lagged values of the predicted index but in this paper different indices and market variables are chosen as inputs instead in order to improve the network performance.

Kara, Boyacıoğlu and Baykan (2011) predict the stock price index movement direction using both artificial neural networks and support vector machines. Ten technical indicators were used as inputs of the models. It is claimed that predictive performance of the artificial neural network is significantly higher than the support vector machine model.

Çinko and Avcı (2007) compare neural network and linear regression forecasts of the ISE-100 index. The comparisons are made using mean squared error, normalized mean squared error and trend accuracy measures. Non-linear neural network models are found to be better in forecasting than linear regression.

Yümlü, Gürgen and Okay (2005) compare global, feedback and smoothed-piecewise prediction models with the help of multilayer perceptron, recurrent neural network and mixture of experts structures respectively. It is argued that smoothed-piecewise neural model is better in capturing volatiliy when compared to the other two models and the traditional EGARCH model.

Boyacıoğlu and Avcı (2010) adopted an adaptive neural fuzzy inference system to predict the stock market return on the ISE-100 index. It is claimed that monthly return of the ISE-100 index can be forecasted with a very high accuracy. Root mean squared, coefficient of multiple determinations and coefficient of variation of the model are calculated as 0.0068, 0.9827 and 45.8163 respectively.

There are many other papers that apply artificial neural networks to finance. Mizuno, Kosaka, Yajima and Komoda (1998) apply neural networks to technical analysis of stock market prediction and propose a new learning method to improve prediction accuracy. Çelik (2010) compares the predictibality of discriminant analysis and neural networks in determining financial failure probability of banks in the Turkish banking sector. Bildirici and Ersin (2009) use artificial neural networks to enhance the ARCH/GARCH models and propose a ANN-APGARCH model.

3) Methodology

3.1) Artificial Neural Networks

Artificial neural networks try to mimic the working principles of biological neurons in the brain. The biological neural networks are extremely complicated. A typical biological neuron has a cell body, dendrites and an axon. Signals from a neuron are sent through the axon of the neuron and received through one of the dendrites. Synapses are the gaps between neurons. Neurotransmitters are released from the sending side in the synapse and received by the neuroreceptors of the receiving side. Neurons are excited while the learning process takes place in the synapses.

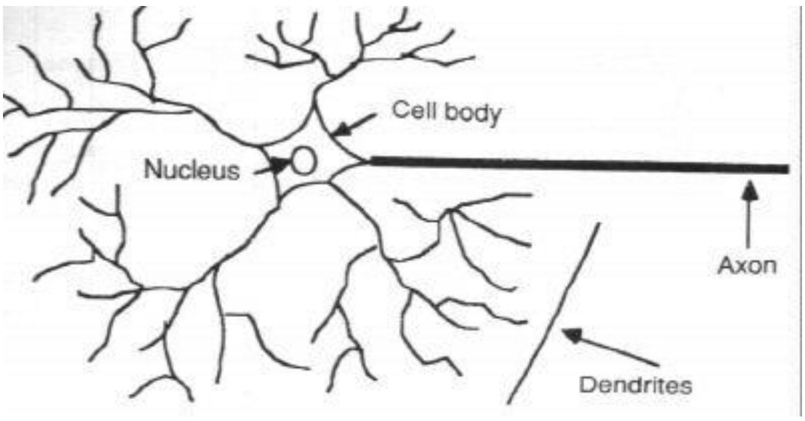

Figure 1: Biological Neuron

Source: jmvidal.cse.sc.edu, retrieved on 28/09/2011

In an artificial neural network, artificial neurons are stimulated with activation functions. The arguments of the functions are the sum of weighted inputs and a bias. In a supervised learning model, the outputs are compared with targets and the network is trained using a training algorithm to adjust the weights such that the error terms satisfy a given minimum.

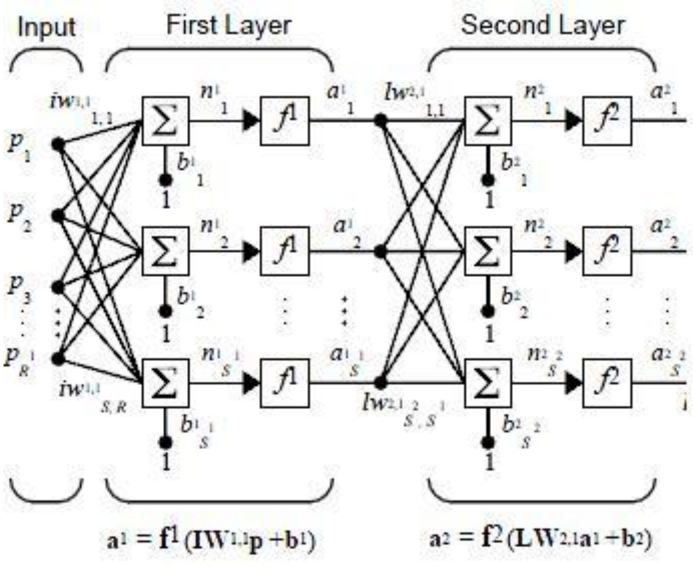

Figure 2: Artificial Neural Network, R= # of Inputs, S= # of Neurons

Source: Demuth, Beale (1998)

3.2) Data

The input vector of a neural network is one of the most important factors that determine how well the network makes forecasts. The inputs of the model are given as follows;

USD/TRY exchange rate,

interest rate of the benchmark Turkish bond,

Dow Jones Industrial Average Index,

German Dax Index,

price of the Brent oil,

and price of gold.

Data series are obtained for the last five years. The period is between 22/08/2006 and 22/08/2011. There are 1150 data points in the data set for each varible. %80 of the data set is used for training and %20 of the data set is used for testing.

3.3) Artificial Neural Network Model

In this paper, a multilayer feedforward backpropagation network is used. The network has one hidden layer and one output layer. The activation functions are chosen as tan-sigmoid and linear because this structure can approximate any function, with a finite number of discontinuities, arbitrarily well.

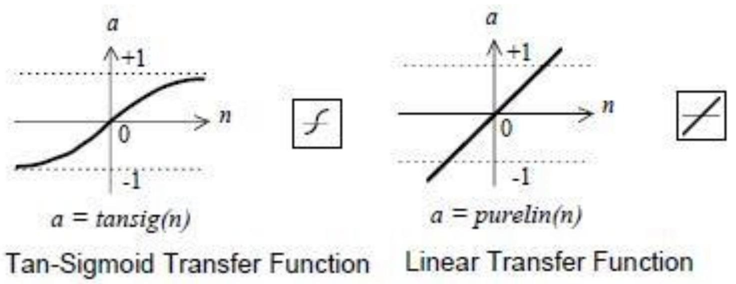

Figure 3: Activation functions

Source: Demuth, Beale (1998)

Returns of the ISE-100 index are given as the targets of the network. Next day's return of the index is given as the target for any given day.

Four networks are constructed in this paper. In the first two networks, the normalized values of the indices and prices are used directly as inputs and targets as in the previous studies. In the last two networks changes of the index values and prices are used as inputs and targets.

In the first and third networks, the targets of the models are the differences between closing prices of the ISE-100 index as in the previous studies. In the second and fourth networks the targets of the models are the difference between the opening and the previous day's closing of the index.

Levenberg-Marquadt is chosen as the training algorithm of the network because of its speed advantages. In order to evaluate the prediction capability of the artificial neural network, the predictions of the model are compared with the real data in terms of both direction and magnitude.

4) Results

The first two networks were able to forecast the direction of the return of the index with 49,34% and 56,77% accuracy and the average errors of the predictions were 1,65% and 1,38% respectively. These results are consistent with previous studies. For example, Egeli, Özturan and Badur use interest rate, previous day's index and TRY/USD values and they were able to predict the ISE-100 index with accuracies from %1,62 to %1,71.

In the third and fourth networks, the direction of the return of the index was forecasted with 55,46% and 63,76% accuracy and the average errors were 1,28% and %0,50 respectively. The error terms are lower than those in the first two models.

From those results it can be concluded that using changes of the variable values as inputs instead of using values directly increases the accuracy of the predictions. The networks worked also better in forecasting the close to open differences than forecasting the close to close differences.

5) Conclusion

Artificial intelligence is a promising field for finance applications. Especially artificial neural networks can be used while making investment decisions. Academic works on the subject contribute to the advancement of the financial markets. Quantitative investment strategies are still at novice level in Turkey. Artificial neural network models may be a way for investors who want to utilise quantitative methods effectively to generate alpha.

In this paper multilayer feedforward backpropagation networks are used to forecast the return of the ISE-100 index. Using changes of values instead of values as inputs and shortening the time gap between the inputs and the targets lead to more accurate forecasts. The findings of this paper can be a framework for an artificial neural network that can be applied as a quantitative investment tool in the Turkish stock market. Further research can be made to study whether shortening the gap between the inputs and the targets further with a high frequent model helps improve the forecasts of the artificial neural networks.

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