COMPARISON OF BAYESIAN ESTIMATION AND NEURAL NETWORK MODEL IN STOCK MARKET TRADING

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ABSTRACT
In this study, a decision support system for stock market prediction is proposed. This model uses the historical data of 180K data points obtained from the 215 highest volume ETFs that are open for trade in NYSE. The data is analyzed with several different criteria such as next 1,2,3,4,5 days percent increase/decrease, percent moves with respect to 50/200 day Moving Averages, changes in RSI, MACD values, direction of movement within Bollinger Bands, etc. The next day prediction is made by statistical analysis on the data using a Bayesian Maximum Likelihood decision model and the best course of action (which ETF is most likely to increase its value) is identified. The training data for the model is the historical data of these ETFs between 1999 and 2006. With the trained network, 2007 data has been tested and the results are analyzed. In order to compare the performance of the model, a multilayer perceptron neural network is developed using the same training and testing data and the results are compared. For performance evaluation, both models analyze which ETF is most likely to create the best short term (1 day – 5 days) rate of return and perform buy/sell decisions accordingly. The results indicate that both models can be used in stock/ETF selection in short term stock market trading, however neural network model provided better results.

1. INTRODUCTION

Forecasting is an important issue when people have to decide under uncertainty. However, forecasting is more important in financial markets since “time is money” in financial analysis [1]. Therefore, forecasting has been a very popular approach for a great number of investors and analysts, since there is a great deal of income/loss within the market.

The forecaster has two main problems, each of which are, when to buy/sell stocks and which stock to buy. This led analysts to investigate and find better methods for forecasting. One approach was to evaluate and analyze the basic financial indicators of the companies in the market such as fiscal situation, position in the market and income-outcome data. However, this alone, was not adequate enough to make relatively correct decisions. Thus, new methods and indicators were invented in order to increase the chance of success of the correct prediction in the financial markets. Technical analysis indicators and neural networks are among some of these techniques which are most commonly used in forecasting the stock market movements.

2. TECHNICAL ANALYSIS

Technical indicators are the results of statistical data of stocks and ETFs which are obtained through various mathematical operations and calculations. Although interpretation of the technical analysis data may differ among the experts, the results are usually similar as technical analysis depends on time-series analysis [2]. Technical analysis mainly aims to identify the trend movement of stocks with the help of charts. It also helps to predict and/or visualize the future trend of the financial markets [3].

Technical analysis does not use the financial status of the companies or the market conditions, but rather, uses the open and/or close values, volumes, support-resistance points of the stocks. Technical analysis can be divided into two groups as indicators following the trend and oscillators. Indicators such as SMA, EMA reflect the trend direction and strength in the markets. When the current trend in the market is strong, it indicates a “buy” signal and when the trend is weak, it indicates a “sell” signal for the investors. Oscillators, on the other hand, reflect the percentage of buyers and sellers in the market. The oscillator values differ between an upper and lower bound. When the oscillator value is closer to the upper bound (overbought situation), the number buyers in the market is major and a decrease in the prices is most likely to occur and when the oscillator value is closer to the lower bound (oversold), the number sellers in the market is major and an increase in the prices is most likely to occur. Most commonly used oscillators are PO, RSI, MACD, BB, Momentum, and Stochastics.

3. NEURAL NETWORKS

One of the tools human being developed in order to investigate and mimic natural phenomena is ANN. ANNs are the computer programs designed on the basis of human brain and the neural system. ANNs contain simulated neurons which are interconnected and these neurons form the neural net. These nets have the ability to learn, memorize, and discover the relations among the data. In short, ANNs are used in the problems requiring natural skills of mankind such as thinking and observing.

Stock market forecasting is one of the important application areas where neural networks are applied although it is a challenging problem due to the noise in the input data and the difficulty in producing meaningful inputs for the net [4]. Generally, past close values are used as inputs for the ANNs; however, some researchers prefer to use technical indicator data in order to forecast the future values of the stocks. The NN model may also differ as there are numerous models. Some researchers use ANNs including fuzzy logic [5], [6], [7], [8], [9] where some researchers prefer to use genetic algorithms [10], [11], Support Vector Machines [12], [13] or Hidden Markov Model [14].

5. MODEL DESIGN

In this study two different models, one statistical, the other neural network based, are proposed for stock market forecasting.

The data used in both models are obtained from the daily adjusted close values of 215 highest-volume ETFs in NYSE. The calculated technical analysis indicators of the ETFs are divided into two as training and testing sets in the Bayesian model, and are divided into three as training, validation, and testing sets in the ANN model.

The training set consists of data between the start dates of each ETF and December 29, 2007. The test set is between January 1, 2007 and April 25, 2008.

In the neural network model, the training dates are shortened to a certain degree in order to make all ETFs start and end at the same time. Also some part of training data was used for cross validation.

5.1 Bayesian Estimation with Technical Analysis Model

In this model, a decision support system for stock market forecasting is proposed. This model uses the historical data of 180K data points obtained from the 215 highest volume ETFs. The data is analyzed with several different criteria such as next 1,2,3,4,5 days percent increase/decrease, percentage moves with respect to 50/200 day Moving Averages, changes in RSI, MACD values, direction of movement within Bollinger Bands, etc.

The next day prediction is made by statistical analysis on the data using a Bayesian Maximum Likelihood decision model and the best course of action (which ETF is most likely to increase its value) is identified. The training data for the model is the historical data of these ETFs between 1999 and 2006 which varies according to the start date of ETFs. With the data used for training, the decided rules which were calculated and obtained from the historical data of these 215 ETFs, in other words, the Bayesian decision model were applied to the 2007 data and the results are analyzed.

5.2 Neural Network Model

Although the Bayesian model uses 215 ETFs, NN model uses 70 most common and long-lasting ETFs and their technical analysis data. In the ANN model, several different network topologies were analyzed and the Jordan/Elman Network was selected as it gave the best results. The layer nodes were selected as 5 input neurons consisting of technical analysis data, 20 neurons in the one and only hidden layer, and 1 neuron in the output layer. Sigmoid function was selected as the transfer function in all layers and MSE minimization was selected as the learning method. The conjugate gradient learning was used as accelerator during the learning phase of the model.

The input layer of the system consists of 5 neurons which are selected from the technical analysis data of 70 ETFs. The output neuron represents the percentage difference of an ETF's adjusted close value and twenty-day EMA value. The model was trained until the average MSE reached to an acceptable level of 0.001245 in around 250 epochs in the best resulting network.

5. TEST RESULTS

When the test results are analyzed it was observed that both trading strategies performed better than the BHM. Neural network model was particularly outperformed the other two and for some ETFs the annual percentage profit was over 100%. BDM outperformed BHM in 134 out of 215 cases, whereas in only 2 out of 70 cases BHM performed better than the Neural Network model. The performances of the models are compared in Table 1.

	Bayesian Decision Model (BDM)	**Buy and Hold Model (BHM)**	**NN Model**
# of ETFs with the better result in BDM	133 (%62)	82 (%38)	-
# of ETFs with the better result in NN	-	1 (%2)	69 (%98)
max difference (BDM vs BHM)	DCR (21,73 %)	DCR (-80,40%)	-
max difference (NN vs BHM)	-	IGW (-31,1%)	IGW (90,12%)
max difference (BHM vs BDM)	SLX (50,54 %)	SLX (119,80 %)	-
max difference (BHM vs NN)		ICF (20%)	ICF (15%)
Average Profit per ETF	11,73%	9,07%	52,35%
Max Loss	ITB (-31,9%)	DCR (-80,40%)	None
Max Profit	FXI (111,37%)	SLX (119,80 %)	EWK (109%)

Table 1 – Comparison of BDM-BHM and NN-BHM independently

6. CONCLUSIONS

In this study, two stock market prediction systems, Bayesian Decision Model and Neural Networks, were developed and their results were compared. The BDM used the historical data of ETFs in NYSE and technical indicators of these data and tried to predict the next day on the basis of rules which were decided during the training phase. In the NN model, these technical data were given to the network as input, and the network was asked to predict the next day on the increase/decrease basis. Although the life span of training data varied, each ETF had a minimum life-span of 2 years. This enabled the network to learn not only the increasing or decreasing trends, but also the times where no obvious trend could be observed.

The proposed models used the ETFs in NYSE which were more resilliant to the social effects and company specific events. On the basis of success rates, it wa observed that both models performed better than the Buy-and-Hold strategy..

The results of both models indicate that these two models are superior the Buy-and-Hold model, and they can be used as a decision making model in the stock markets. The results also show that, NN has performed better than BDM which may be used in the first place.

In the future, the stocks in NYSE will be included in the model and tested. Since the stocks are more vulnerable to the company and market specific issues, the stability of the networks will also be carefully monitored.

7. NOMENCLATURE

ETFs : Exchange Traded Funds
SMA : Simple Moving Average
EMA : Exponential Moving Average
NYSE : New York Stock Exchange
MACD : Moving Average Convergence/Divergence
RSI : Relative Strength Index
BB : Bollinger Bands
MSE : Mean Square Error
ANN : Artificial Neural Network
PO : Price Oscillator
BDM : Bayesian Decision Model

8. REFERENCES

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