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The technical indicator Z-core as a forecasting input for neural networks in the Dutch stock market

Gerardo Alfonso

Department of automation and systems engineering, University of Seville, Seville, 41092, Spain

Abstract:

Z-scores are not typically used as a stock forecasting tool but it will be shown in this article that they have some forecasting value used in combination with neural networks when applied to the specific case of the stock market in the Netherlands. The mean error obtained using a network with 500 neurons and the Z-core data for forecasting the direction of the stock market in the following day was 46.2 percent. Multiple networks were tested (with different amount of neurons), for all of them at a 5% significance level the error was below 50 percent. There was also no statistically significant improvement in forecasting accuracy by increasing the number of neurons by 400 times, from 20 to 8000.

Keywords **—machine learning, stocks, Netherlands.**

I. INTRODUCTION

There is a large amount of research work in different areas of stock forecasting. This article focuses on technical analysis forecasting. Technical analysis uses historical values to try to determine the stock price of a company in the future. For historical reasons there is considerable less literature available on technical analysis than in other areas of investing. Technical analysis tends to be done by investors with a highly quantitative background, such as engineers, and it based on the construction of some numerical model, which needs not to be linear. Some very well know and commonly used indicators are moving averages and Bollinger bands. In this article a less frequently used technical indicator, called Z-score, was analysed. Using Z-scores directly for stock forecasting purposes is an area that remains relatively underdeveloped compared to some of the previously mentioned indicators. The Z-score can be defined as the difference, in standard deviations, between the closing level of a stock and a moving average. So, if for example the Z-score for a given day is 1.0 that would mean that the closing level for that given day is 1.0 standard deviations away from the moving average level. It will be shown later in this article that Z-scores, as previously defined, present some, but relatively small, forecasting ability. The relationship between the Z-cores and future stock price movements was considered as being not linear and hence it was chosen to use a simple neutral network as a forecasting tool. Neural networks have been extensively applied in finance.

A neural network is an algorithm that is frequently used for forecasting [1], classification and clustering analysis. The notoriously difficult task of forecasting stock prices can be simplified following a binary approach in which all the model tries to accomplish is guessing if the stock price is going to be up or down in the following day, rather than actually trying to determine the closing price for that stock. In this way the problem of stock forecasting is transformed into a classification problem. There is a vast amount of different neural networks with specialist dedicating fulltime to this type of research. In this article the forecasting is done with a simple supervised learning, backpropagation neural network with one hidden layer. At its core a neural network is just a total that tries to make the error function as small as possible by altering the weights no some functions that receive as input a given variable. In simple terms supervised learning means trying to reduce the value of the error function.

It is not given that the performance of an indicator such as Z-score, used in combination with neural networks, will be necessarily the same across different countries. In this article the stock market of the Netherlands was analysed. The Netherlands has a fully functional stock market. A stock index approach rather that analysing the performance of individuals stocks, was followed.

II. LITERATURE REVIEW

Neural networks are a tool of increasing popularity. They are a powerful tool that tries to mimic, in a clearly simplified way, the functioning of the brain. A network is formed by neurons that are arranged into layers. Neurons are just functions that generate an output after receiving an input. Typically the functions used in artificial neurons are selected so that the output is in the minus one to one range. There is a numerical factor associated with each neuron that can increase or decrease the contribution of those neurons to the actual final value trying to be forecasted. This is the actual process of learning in the neural network. Detailed analysis on general neural networks can be found in for instance [2] and [3]. Neural networks have been successfully applied to many areas, not only finance, such as face recognition [4] or traffic noise management [5].

There are numerous articles covering specific applications of neural networks to stock market predictions, such as [6] and [7]. Neural networks have also been applied to many other areas in finance such as market share prediction [8] and company bankruptcy [9]. Given the enormous amount of combinations possible, when selecting what inputs to use as well as which specific neural network to deploy, it is rather challenging to extrapolate results for different markets. In some cases, the accuracy of the forecast obtained by researchers is rather remarkable. For instance, [10] mentions a 96% accuracy rate for the Nifty index. It should be noticed than in developed markets such as the Netherlands quantitative investment models have been around for a significant amount of time and that it is possible that some of the investing opportunities present in maturing countries such as India might have been fully exploited away in countries such as Holland. This is a relatively simple concept but with deep consequences. It basically means that the investing opportunities present today might not be profitable in the future as more and more investors use them and profits decrease over time.

III. METHODOLOGY

The first step is deciding what index to use. In this case the AEX index was selected. The AEX index is composed by the top 25 companies listed in the Amsterdam Stock Exchange by market capitalization. The daily closing price for a period of over 5 year, from 2011 to June 2017, was selected. Rather than the using the closing price as the output value a calculation was performed to establish if the index, in the following day, closed higher (Category 1) or lower (Category 0). In this way, the problem is transformed from a forecasting problem i.e., predicting the stock value, to a classification problem, predicting if the following day will be an up or down day. The Z-score (250) was obtained calculated according to the formula:

$$Zcore\ (in\ \sigma\ units) = p_i - MA(250)$$

Where

$$P_i = closing\ price$$
$$\mathrm{MA}(250) = 250\ days\ moving\ average$$

In a first instance a backpropagation neural network with 20 neurons was used. It is a well-known characteristic that the accuracy of neural network can be improved in some cases by adding neurons. This improvement, while conceptually appealing, is sometimes cancelled by the issue of over-fitting. Over-fitting in simple terms can be described as the issue of having a model that is able to very accurately forecast the output variable used for training but it is enable to generate good forecast for data not yet seen by the algorithm. In order to explore the impact on accuracy of adding more neurons an asymptotic analysis was carried out. The neural network started initially with 20 neurons increasing it until a maximum of 8,000. At each level 100 simulations were carried out and descriptive statistics were obtained.

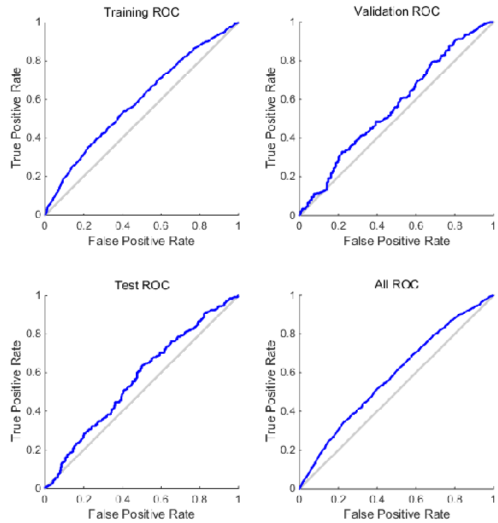

Figure 1. ROC sample – one day out forecasting (Z score)

The error obtained using increasingly large amount of neurons were compared. An Anderson-Darling and a Lillie test were performed on the error to determine if they followed a normal distribution, which at a 5% significance level they did (Table 1 and 2).Confidence intervals for the mean and standard deviation, at a 5% significance level, were then calculated. There was no statically significant difference for the mean (Figure 2) or the standard deviation (Figure 3).

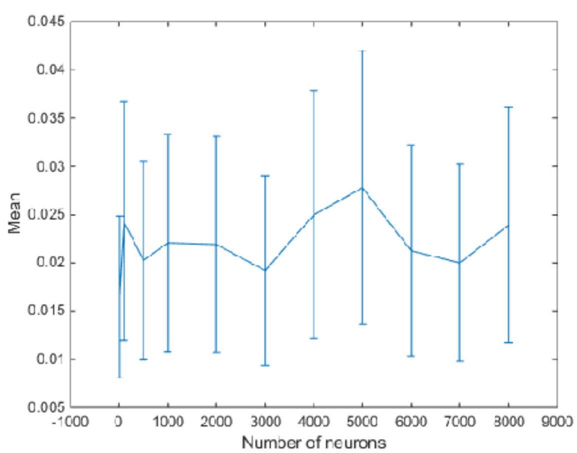

Figure 2. 3. 5% significance confidence interval for mean

IV. CONCLUSIONS

The Z-score directly used as a forecasting tool for the stock market has some predicting value when applied to the Dutch stock market. That predictive a value is small but statistically significant. The average error for misclassification of the direction of the stock market in the following day that the Z-core is utilized was (mean), for a neural network with 500 neurons 0.462 with a standard deviation of 0.019. This standard deviation and median were obtained by doing 100 neural network simulations. The model seemed largely insensitive to increases the number of neurons (Figure 2). The number of neurons in the network was increased from 20 to 8000 to analyze the asymptotical behavior. A Lillie test and an Anderson-Darling test were performed for the error distributions obtained using networks with different amount of neurons (Table 1 and 2) in order to determine of the distribution followed a normal distribution.

Number of neurons	P	Number of neurons	P
10	0.137	4000	0.500
100	0.500	5000	0.500
500	0.500	6000	0.500
1000	0.493	7000	0.500
2000	0.500	8000	0.160
3000	0.128		

TABLE I. LILLI TEST FOR THE ERROR DISTRIBUTION

According to the results from both tests the hypothesis that the data follows a normal distribution cannot be rejected at a 5% significance level. The results for both tests are consistent with each other. At a 5% significance level there seems to be no statistically significant difference for the mean value of the error regardless of the amount of neurons used (Figure 2). There is also no significantly statistical difference of the standard deviation for the error among the different networks (Figure 3). A 400 times increase in the number of neurons, from 20 to 8000 neurons, seems to have very little impact on the accuracy of the forecast. Regardless of the network used the error was, at a 5 percent significance level, below 50 percent for all the cases. Similarly there was no statistically significant difference for the standard deviation of the multiple networks.

Number of neurons	P	Number of neurons	P
10	0.455	4000	0.807
100	0.990	5000	0.527
500	0.544	6000	0.973
1000	0.765	7000	0.891
2000	0.872	8000	0.254
3000	0.264		

TABLE III. ANDERSON-DARLING TEST FOR THE ERROR DISTRIBUTION

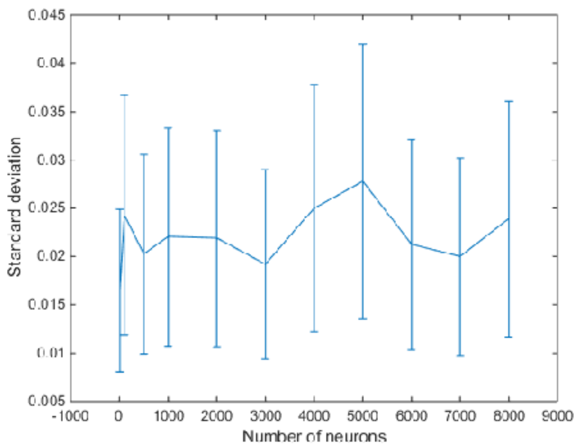

Figure 3. 5% significance confidence interval for standard deviation

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