AlphaB3 – Expert Advisor using Artificial Neural Networks and Genetic Algorithms to Predict Stock Market Trends

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Abstract. *The comprehension of the relation between stock market's nature and a country's economy is an essential part of the components of any financial decision-making system. This paper describes the steps to build an Expert Advisor (EA) named AlphaB3, specialized in stock trading in brazilian financial market. AlphaB3 uses neural networks and genetic algorithms to buy or sell financial assets dynamically based on the stock value variation. According to the evaluations of AlphaB3, when a neural network is trained with sufficient data, the created mechanism guides the investor to buy or sell with a higher profit than if it uses an EA based on an alternative rule.*

1. Introduction

The financial market is one of the main mechanisms to boost the economy of a country. It is formed by the monetary, credit, exchange and capital market. The latter supports productive economy agents in medium and long-term financing. The stock market integrates all the operations made at the stock exchange and is influenced by many external factors, such as politics, foreign-exchange reserves and financial crisis. This type of interference gives a dynamic aspect to this market, making it unpredictable because of its fluctuation (which may cause profit loss) [Lund et al. 2012].

The prediction of stock index is an important objective aimed by investors. It allows to make the best decision during the process of buying or selling of stocks. Therefore, the investors can assume many trading profiles (i.e. fundamentalist, technical or momentum) during the decision-making process. According to [Lam 2004], the fundamentalist analysis assumes that an open capital company's financial vitality is extremely important when it comes to investing. On the other hand, the technical analysis considers the trends of prices during past and tries to identify patterns in fluctuation measurement of future prices.

To invest in foreign exchange and stock markets, technical analysts typically make use of the MetaTrader, an online platform which offers a group of functionalities that can help in the trading process, especially with the display of technical indicators in charts at real time [MetaQuotes Softwares 2018]. Furthermore, it allows to create custom trading

robots, called as Expert Advisors (EAs), to help users with investing automation. These robots can use technical analysis procedures, decision-making adaptive approach to predict price variations and negotiate according to the best option in most of the time. Taking advantage of this scenario, in this paper we propose the AlphaB3, an EA which explores the combination of Artificial Neural Networs (ANNs) and Genetic Algorithm to help investors during the process of buying or selling stocks at brazilian financial market.

This paper is organized as follows: Section 2 presents a brief analysis about Artificial Neural Networks and introduces the concepts related to Genetic Algorithms. Section 3 describes about related works, exploring the performance of robots at financial market. Section 4 describes how AlphaB3 EA works, showing which ANN model was used during its creation. Section 5 then presents the obtained results, explaining the algorithm performance through technical analysis. Finally, Section 6 presents conclusions and discuss about future works.

2. Theoretical Background

2.1. Artificial Neural Networks

There are many algorithms used in the field of artificial intelligence to predict time series informations, especially when the focus is forecasting financial values (e.g. SVM, fuzzy logic and pattern recognition architectures). One of them are the Artificial Neural Networks, actually used by many areas, such as image processing, time series prediction and natural language processing [McEwan et al. 2010, Egmont-Petersen et al. 2002, Tu 1996]. Its focus is to simulate how human nervous system works, including the process of adapting and learning from a dynamic environment [Klerfors 1998].

In Computer Science, ANNs consist of a collection of elements whose inputs and outputs are connected to build a network [Samanta et al. 2003]. The basic unit of a neural network is the processing unit, also called as neuron. Figure 1 shows an artificial neuron model formed by three basic components: a group of input signals, a procedure to perform the sum of these signals and an activation function represented by $f(x)$ [de Souza 2005].

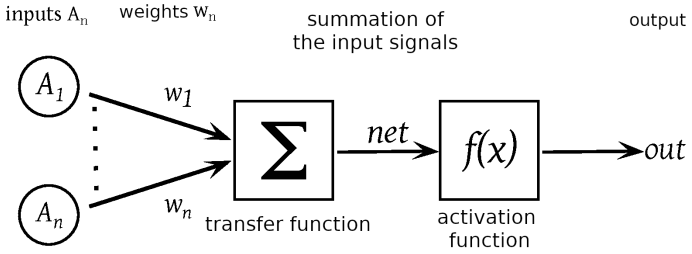

Figure 1. Artificial neuron model.

The input signals are values received through the output of another neuron or through the input data informed by the system or user. Each one of these input signals is associated to weights, which refers to the degree of influence (i.e. the frequency and nature of the transmitted signal) on the input signal of the neuron. These weights, which can be negative or positive values, are normally determined through training [Klerfors 1998].

At (1) the function *net* represents the result of the weighted sum of all the inputs. This sum is made by a procedure and the weights correspond to w. The amount of inputs

and weights is represented by n.

$$net = \sum_{n} x_n w_n \tag{1}$$

A neuron calculates an output called out (as shown in (2)) using an activation function $f(x)$, which considers the weighted sum result. Each neuron contains a non-linear activation function which combines informations of all neurons from previous layers. The output layer is a complex function of inputs and internal network transformation. θ is a threshold value used only by hard-limit functions.

$$out = f(net - \theta) \tag{2}$$

According to [Karlik and Olgac 2011], the main types of activation functions are: Step, Sigmoid and Hyperbolic Tangent. This project uses the latter one (its formula is shown in (3)) to deal with three states of the processed data, which is inside the [-1,1] interval (i.e. buy, sell or do nothing).

$$out = th(net) \tag{3}$$

The learning process occurs after the ANN performs the change of the weights of a neuron. As can be seen in Figure 2, the main ANNs models consist of three parts: one input layer, one or more hidden layers and one output layer. The inputs are inserted into the neural network through the input layer. Then the hidden layers will processing and feed-forwarding this information until the output layer, where the result is obtained.

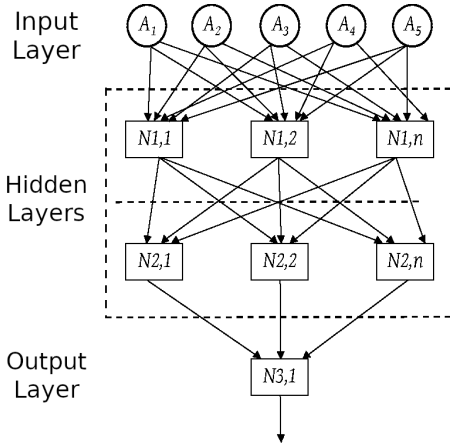

Figure 2. Multilayer Artificial Neural Network model.

Before the feed forwarding process of the ANN, the input data must be normalized, because this process reduces the data to the intervals [0, 1] or [-1, 1]. If this normalization is not performed, the input data will make the neuron act in an imprecise way, leading it to wrong decisions. The data normalization equation can be see at (4).

$$y = \frac{(x - x_{min})(d_2 - d_1)}{x_{max} - x_{min}} + d_1 \tag{4}$$

This paper applies ANNs in stock market, focusing in the process of price prediction [Wang and Wang 2011, Kuo et al. 2001], combining it with Genetic Algorithms to adjust and balance weights until the neural network always finds the best solution given any input data.

2.2. Genetic Algorithms

Genetic Algorithms are actually applied in many different areas (e.g. profit management of companies, prediction of ANNs structures on the bioinformatics area, mathematical finance). In this paper, these algorithms will be used for training artificial neural networks [Goldberg and Holland 1988]. A Genetic Algorithm is a search mechanism based on genetics and the laws of natural selection. It basically has three genetic operators: selection, crossover and mutation, organized in a cycle that is ended after the selection of the best chromosome collection (i.e. possible solutions for a problem). As shown in Algorithm 1, this process starts with a set of individuals which is called population (line 2). Each individual is characterized by a collection of parameters (i.e. variables) known as genes. A chromosome (i.e. solution) is formed by the union of these collections.

Algorithm 1 Genetic Algorithm pseudocode.

```
1   begin    {
2      generate population
3      calculate fitness
4   repeat
5      select population
6   crossover
7      change population
8      calculate fitness
9   until the population converges  }
10   stop
```

In a Genetic Algorithm, an individual gene collection is represented by a string built based on one alphabet with binary values. This collection is codified in a chromosome. The fitness function determines how an individual is suitable (i.e. its capacity to compete with other individuals). At line 3 of the Algorithm 1, this fitness function value is given to each individual. The individual's probability to be chosen is based in your physical score. The objective of the selection phase is to identify the more fit individuals and let then transmit your genes to the next generation. Two pairs of individuals (i.e. parents) are selected based on your physical fitness. Individuals with a higher fitness value have more chances to be selected for breeding. At line 6, the children are generated based on the permutation of the parents genes until the crossover point [Goldberg and Holland 1988]. In this specific moment, the new generation is included to the population (line 7). In some cases, there are some individuals of this new generation which are submitted to a mutation with low random probability. It implies that some bits in the string may have be inverted. The mutation process happens to keep the diversity in the population and prevent an early convergence (otherwise one wrong solution is given as result). At line 9, the algorithm finds its end when the population converges (i.e. there are no new descendents). Thus a collection of solutions is generated.

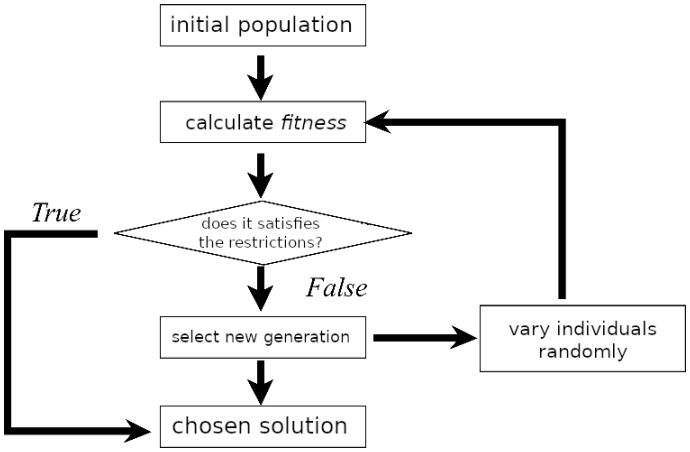

Figure 3. Genetic Algorithm flow diagram.

The population has a fixed size. Individuals with lower fitness are excluded as the new generations are formed, giving space to the new children. The phase sequence is repeated to produce better individuals in each new generation [Tang et al. 1996]. Figure 3 shows the Genetic Algorithm flow diagram [Whitley et al. 1990].

Our proposal involves using these algorithms to balance the ANN weights, calibrating their values before the Expert Advisor initialization, based on a training process and determining the best initial weights according to the provided best solutions (i.e. the ones which provide the greatest possible profit in the training). During the EA runtime, these values are updated according to the neural network evaluation.

3. Related works

Soft computing [Zadeh 1994] is a correlated expression for artificial intelligence. Models based on soft computing include techniques such as artificial neural networks, fuzzy logic and support vector machines [Chaturvedi 2008, Lin et al. 2008]. The area of study of ANNs has wide margin for potential applications, ranging from routine operations of credit assessment up to strategies manipulation in large scale.

Zhang and Wu propose the improvement of the bacterial chemotaxis (IBCO) integrated to a backpropagation neural network to develop a model of index prediction in stock market [Zhang and Wu 2009]. The proposed model aims to predict Standard & Poor's 500 index. The total amount of samples to the stock indexes is composed by 2350 working days, from October 23 1998 to February 27 2008. Each sample consists on the open, close, higher and lower prices, stock volume and the next price after the close. The disadvantage of this method is that it does not support buying or selling assets at B3 (the union between BM&FBovespa and CETIP).

The paper "Stock Market Prediction Using Artificial Neural Networks Based on HLP" presents a method called high-low point (HLP) [Wang and Wang 2011], which is a variant of the method high-low. It is based in the fact that the newly created method HLP works as a data pre-processor to analyze the market stocks. Through the information of high and low points of stocks with different frequencies and amplitudes, an ANN was built to predict the direction of the price movement of Shanghai Composite index. The daily close prices were chosen as samples. HLP method was used to extract high and low

points in datasets between November 18 1991 and February 10 2009. This project does not offer a tool for complete technical analysis. It should be used along with other tool that provides some technical indicator, which will be used to analyze it.

Ticknor proposes a bayesian regularized artificial neural network as a method to predict the stock market behaviour [Ticknor 2013]. The daily market prices and the financial technical indicators were used as inputs to predict the daily close prices of the stocks. The proposed technique suggests the overfitting and overtraining potencial reduction to improve the prediction quality and network generalization. The presented model is based on the Microsoft Corp. and Goldman Sachs Group Inc stocks with samples of 734 working days, between January 4 2010 and December 31 2012. Each sample consists in daily information, including the the trading volume and open, close, high and low prices. According to [Ticknor 2013], the proposed model works as the most advanced models, with no need to pre-process data or cycle analysis.

In the work proposed by [Kuo et al. 2001], an intelligent decision support system focused on stock trading was built with the integration of fuzzy neural networks based on Genetic Algorithms and artificial neural networks. A Genetic Algorithm based on a fuzzy neural network (GFNN) was created to measure the qualitative effect in the stock market and to formulate the knowledge base of fuzzy inference rules. Then this knowledge was integrated to the technical indexes using an ANN. The sample period was between 1991 and 1997. This paper was focused only in the Taiwan stock market.

As AlphaB3 uses MetaTrader, it is easier to integrate this EA with any other stock market. Some of the presented works have proved that neural networks have a good performance in the price prediction task, but there is a need to improve it during its training phase, using Genetic Algorithms to balance its initial weights before inserting it in a real-time trading environment.

4. AlphaB3

AlphaB3 is a specialized stock trading Expert Advisor focused on the brazilian stock market which uses genetic algorithms and artificial neural networks to help in the processes of buying and selling stocks. As one of the requirements of AlphaB3 is the communication with B3, MetaTrader trading platform has been used along with MQL programming language.

4.1. Architecture

Figure 4 shows how the communication between AlphaB3 and B3 happens. It is cloud-hosted to provide high availability and a connection through HTTPS protocol is made with a broker. This broker ensures the connection with B3, where it access the data about the asses (i.e. prices and volume values).

Following the purpose of saving time during the creation of trading strategies, the components of the created EA must be compatible with six basic classes:

- CExpert is responsible for the creation of the trading robot. This class is the place where the trading happens. It deals with the enums ENUM_TRADE_EVENTS and ENUM_TIMEFRAMES, using instances from CIndicators, COrderInfo, CPositionInfo, CExpertSignal, CExpertTrade, CExpertTrailing and CExpertMoney classes.

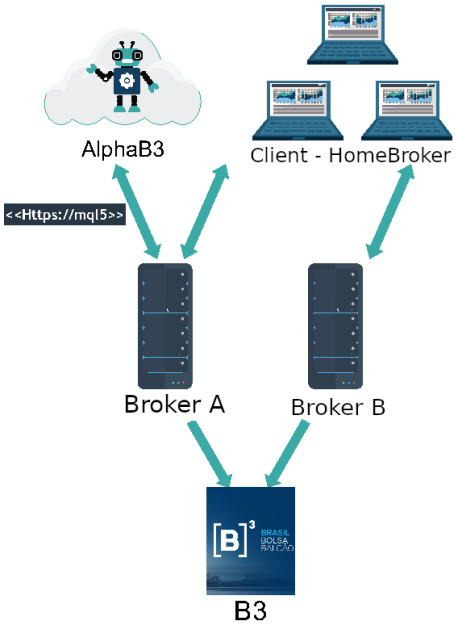

Figure 4. Communication between AlphaB3, brokers, homebrokers and B3.

- CExpertSignal creates the trading signal module.
- CExpertTrailing is used to watch the Stop-loss value (i.e. an automatic order to sell an asset when it is below a certain price).
- CExpertMoney manages the invested money.
- CExpertTrade derives from CTrade and access the trading functions.

Each Expert Advisor is composed by four basic blocks (or methods): parameters block, $OnInit$, $OnDeInit$ and $OnTick$. There are two other blocks ($ActivateNeuron$ and $CalculateNeuron$) to represent the specific functions of the AlphaB3 algorithm. The variables to identify the EA's author, a short description and the EA's version are stored at the parameters block. Other variables such as vectors and indicators are declared at the $OnInit$ block. $OnDeInit$ block is responsible for the exclusion of variables, vectors and indicators. It is called when the starting process is unsuccessful or when the EA is finalized. Finally, $OnTick$ block controls how the EA will proceed when some new information about the current symbol (the traded asset) is received in the server.

Before starting the Expert Advisor, there is a training process to determine which are the best initial weights for it. This process is made to test the EA behaviour with previous data of the selected asset. This data is available at MetaTrader, which allows to train (or test) our EAs with it, estimating how the trading strategy will work when inserted in a real environment. Genetic Algorithms are used during this step to calibrate these values, testing with multiple values of weights and choosing the best ones that have provided the greatest profit during the training phase.

As the Expert Advisor trading decisions are based on ANNs, the $CalculateNeuron$ and $ActivateNeuron$ blocks were created. The first one uses a variable to store the weighted sum of the inputs, processing this value in an activation function (i.e. $ActivateNeuron$ block). This function will return the output value to the

$OnTick$ block.

5. Obtained results

The computer used to execute the AlphaB3 evaluation has the following configuration: Intel®Core™i3-3227U CPU @1.90GHz, 4.00GB RAM and the Windows 7 64 Bits as operating system. The data was accessed through the MetaTrader platform, using an individual account registered in the XP Investimentos CCTVM S/A broker. The data was analyzed in two different time periods: two years (from March 21 2016 to March 21 2018) and one year (from March 20 2017 to March 20 2018). Petrobras (PETR4), Itaú Unibanco (ITUB4), Vale (VALE3) and Companhia Siderúrgica Nacional (CSNA3) were chosen as the stocks to be analyzed. The first three are considered as the most traded stocks in Brazil during the year of 2017 [Bartolo 2017].

The results of the evaluations of all the data series in one and two years show that the quality of the historic data was 94%. This percentual is an indicator which shows the quality of the tested data. It is the result generated through the correlation between the correct and incorrect momentary data. Historical omissions and data with zero spread are considered as incorrect momentary data. Despite the initial value of each asset was configured as R$ 100.000,00, the AlphaB3 only used a fraction of it at the buying moment. It repeated during all the evaluations.

Table 1. PETR4, ITUB4, VALE3 and CSNA3 trading analysis.

	PETR4		**ITUB4**	
Period	**Initial**	**Profit**	**Initial**	**Profit**
Two years	R$ 1.556,00	R$ 1.164,00	R$ 9.994,00	R$ 4.598,00
One year	R$ 3.774,00	R$ 579.00	R$ 3.250,00	R$ 920,00
	VALE3		**CSNA3**	
Period	**Initial**	**Profit**	**Initial**	**Profit**
Two years	R$ 4.926,00	R$ 4.134,00	R$ 3.533,00	R$ 1.942,00
One year	R$ 10.766,00	R$ 2.506,00	R$ 8.996,00	R$ 2.939,00

5.1. Comparison with MACD

MetaTrader platform has a collection of pre-created Expert Advisors, configured to act according to technical indicators. An optimization in a pre-created EA, which works based on Moving Average Convergence / Divergence (MACD) rule [Yazdi and Lashkari 2013], was made. This rule is able to show the relationship between prices and moving averages, being one commonly used technical indicator and used in this project to compare its performance with AlphaB3. The optimized parameters are: fast moving average period, slow moving average period and the period of calculation of the differential average.

During three of the MACD evaluations in one year period series, there was a gross loss. In addition, many orders were realized on the PETR4 and ITUB4 stocks. This quantity of transactions makes the trading process more computationally expensive. Then the tradings made by the MACD with a profit higher than the ones earned by Alpha3 end up being nullified or its profit value is lower than the proposed to the EA. One example of this scenario is the profit earned during PETR4 stock tradings by MACD of R$ 638.00

compared to the R$ 579.00 of AlphaB3. Evaluations with data series which covers the two year period totaled more than 90 buy and sell orders for ITUB4 stocks. In this case the investment got a loss of R$ 541.00.

6. Conclusion and future works

This paper proposed an EA which uses an artificial neural network to guide the user to buy or sell stocks. The proposed ANN predicts the price revert moment and uses a group of trading rules to alert the investor about which is the best moment to do buy or sell. The proposed system was tested using the data from B3. Trades have been done considering the four stocks with biggest financial volume in B3 (i.e. PETR4, ITUB4, VALE3 and CSNA3). The evaluations showed that ANNs can predict stock market values when trained with sufficient data, optimized inputs (generated by Genetic Algorithms) and with an appropriated architecture. The results were compared with the ones generated by the MACD Expert Advisor and, in a general way, the AlphaB3 showed to be more precise, earning a higher profit and following the best trading options.

AlphaB3 included many real-world restrictions during its processing time, whereas these restrictions are ignored by other trading systems. However, the highest profit in the lower quantity of transactions where considered to avoid unnecessary expenses with taxes. Furthermore, it is observed that there were no gross loss in any of the AlphaB3's evaluations. This is important for any investor which intent to avoid profit loss.

Technical indicators can be explored to improve AlphaB3, including them in the algorithm's routine. Also there are other techniques and fields of artificial intelligence, besides ANNs and Genetic Algorithms, such as sentiment analysis (to extract subjective information from the web about a specific stock or asset, which can help in the decision process) and Deep Learning (to execute the training with a higher amount of data), that can improve the decision-making process of Expert Advisors. These topics will be explored as future works in this project.

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