# ON THE USE OF NEURAL NETWORKS FOR STOCK PRICE FORECASTING

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***ABSTRACT***
*Having the ability to predict the price of a particular stock share is undoubtedly a major challenge, because of the complexity and implied volatility of the financial markets. This is a topic of great interest to researchers and market players, as the effectiveness of the forecast might translate into huge monetary gains. This work aims to demonstrate the use of neural networks for stock price forecasting. Two financial titles are considered: Microsoft and Apple. The initial choice of the predictor variables comprises the most used and referenced in the scientific papers published on this subject. This work demonstrates the importance of a careful selection of some of those variables for a good neural network performance.*
***Keywords:*** *Financial markets, neural networks, stock share, variable selection*

## 1. INTRODUCTION

Mankind has always had the desire to foresee the future. Is it possible to forecast a stock price? This is a complex problem, as markets are characterized by their dynamic nature and unpredictability and fluctuate quickly in very short periods (Nigam, 2018). The political climate, the trading wars between countries and several other factors, namely economic, make it difficult to invest with a low risk using only fundamental and technical analysis. Trading on the stock market uses different methodologies for price forecasting and machine learning techniques, which include artificial neural networks, are the most used for this purpose (García et al., 2018). Over the past few decades, neural networks have been widely used in the business area, namely in supporting decision making. Having confidence in a decision support system has become an essential factor for companies and neural networks have advantages when compared to more traditional models, particularly in situations where the data are complex and the phenomena non-linear (Tkác & Verner, 2016). Their learning capacity and their parallel and hierarchical structure are two essential characteristics for solving problems that could not otherwise be solved (Cortez and Neves, 2000). There are several studies referring to the use of neural networks with applications in areas such as auditing, accounting, consumer behavior, foreign exchange markets and financial bankruptcy (see (Tkác & Verner, 2016) and references therein). Lately, financial analysts, managers and researchers have shown interest in the technical analysis of stock prices using neural networks, as they have the ability to recognize hidden indications of when the stock price will rise or fall (Nigam, 2018). For instance, Zahedi et al. (2015) developed several models with accounting variables to forecast Tehran Stock Exchange prices. The authors concluded that neural networks are superior to other models and that they are able to accurately forecast stock prices. Muntaser et al. (2017) applied neural networks to forecast the price of three shares in the oil and gas sector of BM&FBOVESPA. In their study, they used variables related to the stock price, moving averages, bollinger bands, volume, Momentum (MOM) and the Relative Strength Index (RSI), among others, and concluded that the networks are good in forecasting the price. Qiu and Song (2016) used a neural network to predict the Nikkei 225 index, which is the most widely used market index on the Tokyo stock exchange. In their study, they used several variables, including moving averages, volume and RSI. Finally, García et al. (2018) used neural networks to forecast the German DAX-30 index. Their results demonstrate that, the greater the number of variables in neural models, the greater the "noise" in the learning process and the worse the performance of the models in terms of forecasting new cases. They created models with different variables, where they used either all the indicators or only 2, 3, 5 and 10 indicators, demonstrating how important it is to correctly select the variables for an effective forecast. This work aims to demonstrate the use of neural networks for stock price forecasting. Based on the information available in one week, we provide a forecast for the next week. Two financial titles are considered: Microsoft and Apple. In our literature review, we found that the predictor variables, *i.e.*, the information used to forecast a stock price, vary a lot from study to study. Furthermore, we concluded that considering more variables doesn't necessarily lead to better forecasting results. For this reason, it is important to select a part of the available variables in order to obtain the best results and, in this context, many authors use a trial and error approach. In this work, we compare two automated variable selection procedures. In the first one, the predictor variables are all the available variables that are not strongly correlated, *i.e.*, that provide independent information for stock price forecasting. In the second procedure, we quantify the importance of all available variables for the forecasting models developed and, using an iterative process, we successively exclude the least important. As far as we know, this second procedure with the measure of importance we considered was never tested in a context of stock price forecasting. The remainder of this paper is organized as follows. Section 2 briefly presents the fundamental and technical analysis usually considered by investors in their investment decisions. Next, Section 3 describes the neural networks used in this work, Section 4 the data we collected and Section 5 our methodology in what concerns developing, evaluating, selecting and applying neural forecasting models. Finally, Section 6 shows our results for the Microsoft and Apple titles and Section 7 presents the conclusions and future work.

## 2. FUNDAMENTAL AND TECHNICAL ANALYSIS

Investors base their investment decision on fundamental and technical analysis. The latter does not deny the usefulness of the former, but gives it little importance, because a price is formed based on the information that reaches the market and which encompasses all the data, expectations, moods and perceptions of the investors (Matos, 2005). Here, we consider short term price forecasting, since our goal is to forecast from one week to the next one. In our literature review, we found that there are few works using fundamental analysis indicators for this type of forecasting (see, for instance, (Koolia et al., 2018; Zahedi et al., 2015)) and that most works use technical analysis indicators (see, for instance, (A. A. Adebiyi, 2012; García et al., 2018; Muntaser et al., 2017; Nandakumar et al., 2018; Qiu and Song, 2016)).

### 2.1. Fundamental analysis

Fundamental analysis includes the study of economy in general, the relationship of the capital market, the sectors of activity and finally the companies. This analysis aims to know the real value of shares, the so-called intrinsic value, in order to determine whether it is low or high, triggering buy and sell orders according to the price. While analysing a company, investors make use of indicators such as the Return on Equity (ROE) and the Price Earnings Ratio (PER) (Matos, 2005; Neves, 2012).

### 2.2. Technical analysis

Technical analysis has the ability to forecast future movements using statistical resources for that purpose. It allows the investor to identify trends and patterns through the formation of prices, thus grounding a correct preference decision (Silva and Nunes, 2017). The decline and rise in the share price are related to certain performance indicators. The most common are the opening price, the closing price, the lowest and the highest prices and the volume of shares traded in the reference period (Nandakumar et al., 2018). Technical analysis uses the graphical representation of price movements over time to observe increases and decreases and when they happen. It is in this monitoring that the buying and selling movements of a certain stock are decided. There are many useful and common tools in price analysis to identify trends. Some of the most used by investors are the Simple Moving Average (SMA), the Exponential Moving Average (EMA), MOM and RSI (Silva and Nunes, 2017).

**3. NEURAL NETWORKS**

Here, we consider multilayer feedforward neural networks (Haykin, 2009; Silva and Alonso, 2020). Let $x_1, \dots, x_n$ be the $n$ inputs and $y^{net}$ the only output of a multilayer feedforward neural network with one hidden layer of $m$ neurons, as shown in Figure 1.

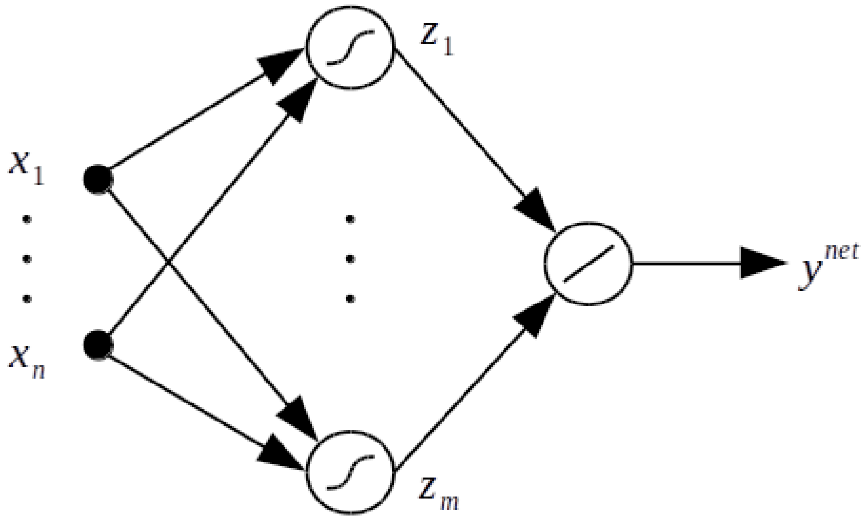


*Figure 1: Multilayer feedforward neural network*
*(Source: The authors)*

The neurons in the input layer do not process data and serve only to forward it to the neurons in the next layer. The neurons in the hidden layer have a sigmoid activation function, namely the hyperbolic tangent. The output of the $i-$th hidden neuron is given by:

$$z_i = g(x_1, \dots, x_n | w_{i1}, \dots, w_{in}, w_{i0}) = tanh\left(\sum_{j=1}^{n} w_{ij}\, x_j + w_{i0}\right), \;\; i = 1, \dots, m,$$

where $w_{ij}$ is the weight of the connection from the $j-$th input neuron, with $j = 1, \dots, n$, to the $i-$th hidden neuron and $w_{i0}$ is a weight called the bias of the $i-$th hidden neuron. The neuron in the output layer has a linear activation function, namely the identity. Its output is given by

$$y^{net} = h(z_1, \dots, z_m | w_1, \dots, w_m, w_0) = \sum_{i=1}^{m} w_i z_i + w_0,$$

where $w_i$ is the weight of the connection from the $i-$th hidden neuron, with $i = 1, \dots, m$, to the output neuron and $w_0$ is a weight called the bias of the output neuron.

Hence, the neural network implements a function

$$y^{net} = f(x_1, \dots, x_n | m, \boldsymbol{w}) = \sum_{i=1}^{m} w_i \, tanh\left(\sum_{j=1}^{n} w_{ij}\, x_j + w_{i0}\right) + w_0,$$

parameterized in $m$, the number of hidden neurons, and $\boldsymbol{w}$, the vector of the $m(n+2)+1$ network weights. The values of these parameters can be determined as explained next.
Suppose that the data available to determine the values of the neural network parameters, $m$ and $\boldsymbol{w}$, are split into two sets: a training set

$$T = \left\{\left({x_1}^{(T,l)}, \dots, {x_n}^{(T,l)}; y^{(T,l)}\right)\right\}_{l=1}^{n_T},$$

with $n_T$ cases, where $y^{(T,l)}$ is the desired output of the network for the input $\left({x_1}^{(T,l)}, \dots, {x_n}^{(T,l)}\right)$, and a validation set

$$V = \left\{\left({x_1}^{(V,l)}, \dots, {x_n}^{(V,l)}; y^{(V,l)}\right)\right\}_{l=1}^{n_V},$$

with $n_V$ cases, where $y^{(V,l)}$ is the desired output of the network for the input $\left({x_1}^{(V,l)}, \dots, {x_n}^{(V,l)}\right)$.

Define the training error as

$$E_T(m, \boldsymbol{w}) = \sum_{l=1}^{n_T} \left(y^{(T,l)} - f\left({x_1}^{(T,l)}, \dots, {x_n}^{(T,l)} \middle| m, \boldsymbol{w}\right)\right)^2$$

and the validation error as

$$E_V(m, \boldsymbol{w}) = \sum_{l=1}^{n_V} \left(y^{(V,l)} - f\left({x_1}^{(V,l)}, \dots, {x_n}^{(V,l)} \middle| m, \boldsymbol{w}\right)\right)^2.$$

Fixing $m = k$, for a certain $k \in \mathbb{Z}^+$, let $\boldsymbol{w} = \boldsymbol{w}^{(k)}$ represent a solution to the non-linear least squares problem

$$min_{\boldsymbol{w}}\, E_T(m = k, \boldsymbol{w}),$$

found by applying a suitable optimization algorithm, like Levenberg-Marquardt's (Rao, 2009). The sequence of the training errors $E_T\left(m = 1, \boldsymbol{w} = \boldsymbol{w}^{(1)}\right), E_T\left(m = 2, \boldsymbol{w} = \boldsymbol{w}^{(2)}\right), \dots$ tends to decrease with $m$, which is a measure of the network complexity (the higher the value of $m$, the greater the network complexity). In turn, the sequence of the validation errors $E_V\left(m = 1, \boldsymbol{w} = \boldsymbol{w}^{(1)}\right), E_V\left(m = 2, \boldsymbol{w} = \boldsymbol{w}^{(2)}\right), \dots$ tends to decrease until a certain value of $m$, say $m = k^\star$, and then starts to increase. In this context, we take $m = k^\star$ and $\boldsymbol{w} = \boldsymbol{w}^{(k^\star)}$ for the neural network parameters.

## 4. DATA

This work aims to demonstrate the application of neural networks for stock price forecasting. The titles selected were the shares of Microsoft and Apple. The choice was due to the fact that they belong to the important technology sector, although other titles from other sectors could have been selected. The problem consists in using neural networks to forecast the price of the financial stocks in a week, based on information about those stocks and the market in the previous week. In this context, it is important to decide on what information should be considered, that is, which predictor variables can provide the best forecasting results. The selection of these variables is not easy. Literature review revealed that researchers don't have a generalized method to select predictor variables. Thus, our decision was to select a set of variables considered in most studies, namely variables related to price, investor sentiments and accounting variables. We collected weekly data from January 8, 2010 to March 8, 2019. Price related data and technical indicators considered in this work were collected through Alphavantage and Yahoo. Sentiments related data were extracted through an Investor Sentiment Survey indicator in Quandl. The indicator measures the percentage of individual investors considered as optimistic, pessimistic or neutral in relation to their market decisions. These feelings were obtained through the American Association of Individual Investors, an independent, non-profit association created with the aim of helping individual investors to become more efficient in managing their own assets. Remark that investor sentiments have been increasingly considered by investors and researchers. Therefore, it becomes important to establish a link between the individual behavior of investors expressed in feelings and the market dynamics. A simple post on a social network can influence the financial market. Thus, the research and measurement of these feelings and the integration of sentiment analysis methods are extremely important in the financial markets (Maknickiene et al., 2018). The variables in Table 1 are the ones we have selected in this work.

| Variable nature | Microsoft | Apple |
|---|---|---|
| Investor sentiment | *Bearish* | *Bearish* |
| | *Bullish* | *Bullish* |
| | *Neutral* | *Neutral* |
| Accounting | *ROE* | *ROE* |
| Price | *Close* | *Close* |
| | *Open* | *Open* |
| | *High* | *High* |
| | *Low* | *Low* |
| | | *Stock Split* |
| Technical indicators | *EMA 15* | *EMA 15* |
| | *EMA 200* | *EMA 200* |
| | *MOM_15* | *MOM_15* |
| | *MOM 200* | *MOM 200* |
| | *RSI 15* | *RSI 15* |
| | *RSI_200* | *RSI_200* |
| | *SMA 15* | *SMA 15* |
| | *SMA 200* | *SMA 200* |
| | *Volume* | *Volume* |
| Index | *Close index* | *Close index* |

*Table 1: Variables by nature/company*
*(Source: The authors)*

The stock split variable was introduced to signal the sharp and sudden drop in price seen only in the Apple title. The values given to this variable were: 1 in the week in which the fall occurred; 0 in the others. As far as we know, no other study has predicted the price of a share including this variable.

## 5. DEVELOPMENT, EVALUATION, SELECTION AND APPLICATION OF FORECASTING MODELS

Given that different variables have values with different orders of magnitude, we started by transforming the data so that all variables would have an average of 0 and a standard deviation of 1. Then, the data were split into three distinct parts: training, validation and test. For a set of predictor variables, the training and validation data were used to determine the weights of the connections between neurons and the number of neurons in the hidden layer. The idea is that, at the end of the training and validation processes, the network parameters are such that the neural model is estimated to have the best forecasting ability with the predictor variables considered. Finally, the obtained network was applied to the test data, with the goal of evaluating its performance when it comes to forecasting cases that were not "seen" before. The number of training cases must be as large as possible and representative of the population (Cortez and Neves, 2000). Thus, the data used for training correspond to the years 2010 to 2016 (weeks 1 to 365), representing 76% of the available cases, the validation data to the year 2017 (weeks 366 to 417) and, finally, the test data to the year 2018 and part of 2019 (weeks 418 to 480). The evaluation of the neural networks was carried out using two performance measures. The first one was the mean absolute percentage error (MAPE), defined as

$$\boldsymbol{MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_i - \widehat{P}_i}{P_i}\right| \times 100\%},$$

where $\boldsymbol{P_i}$ represents the title price in week i of n considered and $\boldsymbol{\widehat{P}_i}$ the forecast provided by the network for that price. The second measure was the hit rate in the price direction, corresponding to the percentage of cases of n considered in which the network correctly predicted a price decrease, maintenance or increase. Finally, the selection of the predictor variables was made according to the following. In a first approach, we started by considering all available variables as predictor variables and, in order to eliminate redundant information, we kept only those that are not strongly correlated, that is, among which Pearson's correlation coefficient is, in module, less than 0.9 (Pestana and Gageiro, 2014). In a second approach, we implemented an iterative process that starts by considering all variables initially available for predictor variables and that, in each iteration, quantifies the importance of the variables to the trained network, leaving for the next iteration only the most relevant ones, with which a new network is trained. The importance of the variables was calculated as in (Alonso and Loureiro, 2015). The software used in all computational experiments was MatLab.

## 6. RESULTS

In the first approach to the selection of the predictor variables, we obtained the correlation matrix between all available variables and excluded the ones that were strongly correlated with the remaining. Thus, we selected 8 variables for the Microsoft title and 13 for the Apple title. For each title, networks with 1, 2, etc. hidden neurons were trained and validated. The training error tended to decrease with an increase in the number of neurons. We stopped training and validating when we verified that the validation error did not improve with an increase in the number of neurons. Thus, the optimal number of hidden neurons was chosen to be the one leading to the least validation error. Finally, the optimal network was applied to the test data. As we can see from Table 2, in the test set, the forecasting error was better for Microsoft (3.5% against 10.3% for Apple), but the hit rate in price direction was worse (38.7% against 53.2% for Apple).

| Stock | Network | Mean absolute percentage error (%) | | | Hit rate in price direction (%) | | |
|---|---|---|---|---|---|---|---|
| | | Training | Validation | Test | Training | Validation | Test |
| Microsoft | 8-1-1 | 2.2651 | 1.586 | 3.4734 | 58.1267 | 45.098 | 38.7097 |
| Apple | 13-1-1 | 3.0677 | 4.7122 | 10.2820 | 50.1377 | 54.9020 | 53.2258 |

*Table 2: Training, validation and test results in the first approach to the selection of the predictor variables*
*(Source: The authors)*

In the second approach to the selection of the predictor variables, we started by considering all available variables, that is, 18 for the Microsoft title and 19 for the Apple title. For each title, networks with 1, 2, etc. hidden neurons were trained and validated and the network whose number of hidden neurons led to the least validation error was selected. The importance of all input variables for the selected network was calculated and the least important ones were excluded. In the next step, networks with the remaining inputs (the most important variables) were trained and validated and the network whose number of hidden neurons led to the least validation error was selected. For the following steps, the least important variables were successively excluded and the remaining ones were kept, leaving only one predictor variable in the end of the process. The results shown in Table 3 refer to the sets of predictor variables leading to the best validation results.

| Stock | Network | Mean absolute percentage error (%) | | | Hit rate in price direction (%) | | |
|---|---|---|---|---|---|---|---|
| | | Training | Validation | Test | Training | Validation | Test |
| Microsoft | 6-1-1 | 2.2481 | 1.2949 | 2.231 | 58.678 | 56.863 | 66.129 |
| Apple | 4-3-1 | 4.7289 | 2.0481 | 3.3121 | 50.4132 | 58.8235 | 51.6129 |

*Table 3: Training, validation and test results in the second approach to the selection of the predictor variables*
*(Source: The authors)*

For the Microsoft title, it was the 6-1-1 network (6 inputs or predictor variables, 1 hidden neuron, 1 output) that led the least validation error. This network was applied to the test data with a forecast error of 2.2%, *i.e.*, 1.3 percentage points less than the error of the 8-1-1 network obtained in the first approach to the selection of the predictor variables. In addition, it should be noted that the 6-1-1 network showed a hit rate in the price direction in the test cases much higher than the 8-1-1 network: 66.1% against 38.7%. Thus, in average, in every 3 test cases, the 6-1-1 network was able to correctly forecast a price decrease, maintenance or increase in 2 cases. Taking into account the enormous volatility of the stock price, this is a very positive result. For the Apple title, the predictive performance obtained with the 4-3-1 network was superior to the one obtained with the 13-1-1 network of the first approach. Note that the 4-3-1 network applied to the test data led to a forecast error of 3.3%, minus 7.0 percentage points than the error of the 13-1-1 network. Also note that the result of the hit rate in price direction was 51.61% against the 53.23% obtained in the first approach. It is possible to conclude that, in average, in each 2 test cases, both networks correctly predict the price direction in only 1 case. Figures 2, 3 and 4 show the observed closing price for the Microsoft title and the forecasts obtained with the 6-1-1 network (second approach) and the 8-1-1 network (first approach) in the weeks of training, validation and test, respectively. In training and validation, the forecasts of both networks are close and estimate well the observed values. However, in the test, the 6-1-1 network forecasts are better than the 8-1-1 network ones, which tends to underestimate the observed values.

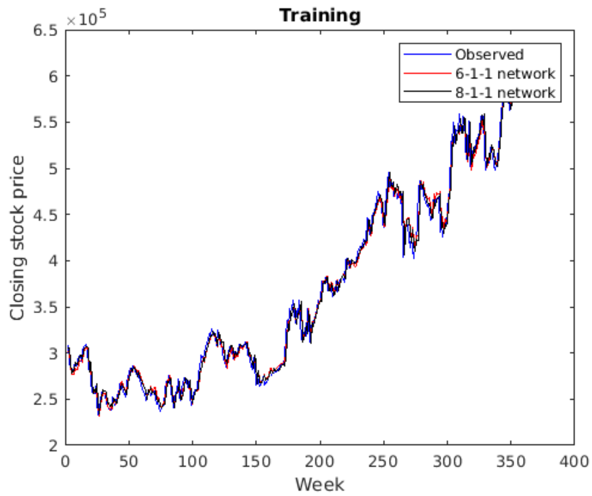


*Figure 2: Training forecasts for Microsoft.*
*(Source: The authors)*

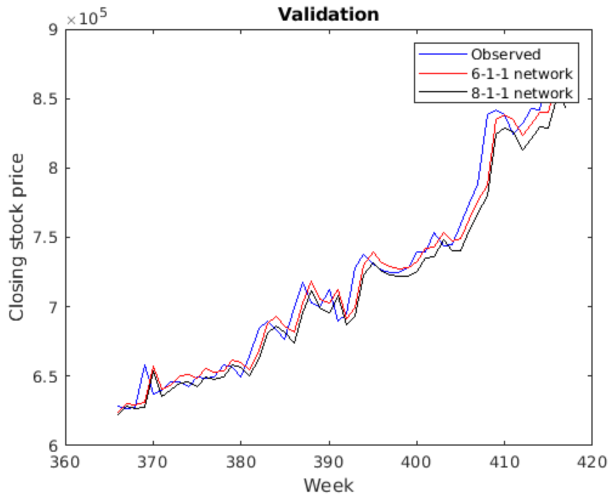


*Figure 3: Validation forecasts for Microsoft.*
*(Source: The authors)*

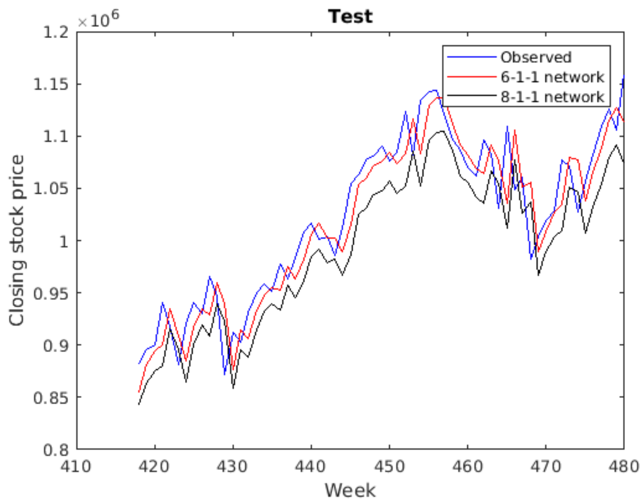


*Figure 4: Test forecasts for Microsoft.*
*(Source: The authors)*

## 7. CONCLUSIONS AND FUTURE WORK

The predictor variables considered by investors, or, in other words, the information they use to predict the price of financial stocks, vary a lot from study to study. Furthermore, considering more variables does not necessarily lead to better forecasting results. For this reason, only part of the available variables should be carefully selected in order to obtain the best possible results. However, in most cases, the selection is carried out on a trial and error basis. In this work, we applied neural networks for stock price forecasting and compared two automated variable selection procedures. In the first one, the predictor variables are all the available variables that are not strongly correlated, *i.e.*, that provide independent information for stock price forecasting. In the second procedure, we quantify the importance of all available variables for the forecasting models developed and, using an iterative process, we successively exclude the least important. As far as we know, this second procedure with the measure of importance we considered was never tested in a context of stock price forecasting. In our experiments, the best results were obtained using this second procedure, both for Microsoft and Apple. We concluded that, regardless of the variable selection procedure, the neural networks tend to give more importance to the variables that are related to the feelings of the investors and less importance to the technical and accounting variables. The best forecasting results were achieved for Microsoft. In the future, we plan to carry out experiments with other titles, from other sectors of activity, seeking to corroborate some of the conclusions obtained in this study, for example, that the predictor variables should be selected based on their importance for the forecasting models. In addition, we would like to consider data with a frequency other than weekly.

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