Enhanced Prediction of Stock Market Analysis

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Abstract: *Stock markets play a major role in the Indian economy. Trading is the most widely used business for many persons in their daily life. Prediction of stock market analysis is very important for the feature business and maintains the business constantly. This is used to analyze the fluctuations and increase trading. Due to the unpredictable nature of stock prices, it is very important to predict the share prices and can improve trading. But manually is highly impossible to predict the market analysis. To overcome this, the enhanced recurrent neural network (ERNN) called Intelligent Term Memory (ITM), where this will predict the market prices and analyze the fluctuations and maintain the accuracy of the result.*

Keywords: ERNN, ITM, stock market.

Introduction

The stock market is a vast array of investors and traders who buy and sell stock, pushing the price up or down. The prices of stocks are governed by the principles of demand and supply, and the ultimate goal of buying shares is to make money by buying stocks in companies whose perceived value (i.e., share price) is expected to rise. Stock markets are closely linked with the world of economics —the rise and fall of share prices can be traced back to some Key Performance Indicators (KPI's). The five most commonly used KPI's are the opening stock price (`Open'), end-of-day price (`Close'), intraday low price (`Low'), intra-day peak price (`High'), and total volume of stocks traded during the day (`Volume').

Modelling and Forecasting of the financial market has been an attractive topic to scholars and researchers from various academic fields. Financial market is an abstract concept where financial commodities such as stocks, bonds and precious metals transactions happen between buyers and sellers. In the present scenario of financial market world, especially in the stock market, forecasting the trend or the price of stocks using machine learning techniques and artificial neural networks are the most attractive issue to be investigated. As Giles et. al [1] explained, Financial forecasting is an instance of signal processing problem which is difficult because of high noise, small sample size, non-stationarity, and non-linearity. The noisy characteristics mean the incomplete information gap between past stock trading price and volume with future price. Stock market is sensitive with political and macroeconomic environment. However, these two kinds of information are too complex and unstable to gather. The above information that cannot be included in features are considered as noise. The sample size of financial data is determined by real world transaction records. On one hand, a larger sample size refers a longer period of transaction records; on the other hand, large sample size increases the uncertainty of financial environment during the sample period. In this research, we use hourly stock data instead of daily data in order to reduce the probability of uncertain noise, and relatively increase the sample size within a certain period of time. By non-stationary, one means that the distribution of stock data is various during time changing. Non-linearity implies that feature correlation of different individual stocks is various [2].

Literature Survey

Nowadays the stock market has been called for research in many fields due to its effects on financial challenging and capacity of forecasting its various aspects through different scientific methods such as genetic algorithm, Artificial Neural Network (ANN) and other Meta heuristic algorithms. Many institution and academic researchers are trying to propose a method for forecasting next day behaviours of stock indexes in order to be better than the other methods, like a research that Majhi and other friends [8] did via applying bacterial foraging optimization technique for forecasting stock market and S&P500 indexes in short and long terms, and they made a linear combiner model which its weights updated by BFO and comparing it with Multi-Layer Perceptron (MLP) based method showed that Majhi and other friend's method has less calculative complexity and more precision to MLP method. Another forecasting system [9] in which counting of complex keyword topples and its transformation to predict stock market behaviour periodically and doing real-time forecasting on web has been done. Some researchers used text mining approach [10], their findings investigate effects of financial news in forecasting stock market. Increasing social networks and their popularity among people have been led into new ideas of investigating of effect of the popularity and application of these social networks that can have on stock market behaviour.

A popular method of modeling and predicting the stock market is technical analysis, which is a method based on historic data from the market, mainly price and volume. It follows some assumptions: (1) prices are defined exclusively by the supply-demand relation; (2) prices change following tendencies; (3) changes on supply and demand cause tendencies to reverse; (4) changes on supply and demand can be identified on charts; And (5) patterns on charts tend to repeat [6]. In other words, technical analysis do not take into account any external factors like political, social or macro-economical. In regards to computational intelligence there are plenty of studies assessing different methods in order to accomplish accurate predictions on the stock market. They go from evolutionary computation through genetic algorithms as exemplified in [7], statistical learning by using algorithms like Support Vector Machines (SVM) [8] and a variety of others including neural networks, component modeling, textual analysis based on news data, that are discussed by [9] which also proposed a new approach based on collective intelligence. Taking a closer look into works related to deep learning in stock markets there are some examples like [10] where a study is made on the usage of a Deep Belief Network (DBN), which is composed of stacked Restricted Boltzmann Machines, coupled to a Multi-level Perceptron (MLP) and using long range log returns from stock prices to predict above-median returns for each day. [11] also use of DBN, but this time using price history in addition to technical indicators as input, in a similar approach to this project. Both of those works present improved results compared to their baselines, as well as in [12] where a survey in deep learning methods applied to finance is made and their improvements discussed.

Enhanced Recurrent Neural Network (RNN) called Intelligent Term Memory (ITM)

Long Short Term Memory (LSTM) networks (Figure 1), which are used in this project are a deep and recurrent model of neural networks. Recurrent networks differ from the traditional feed-forward networks in the sense that they don't only have neural connections on a single direction, in other words, neurons can pass data to a previous or the same layer. In which case, data doesn't flow on a single way, and the practical effects for that is the existence of short term memory, in addition to long term memory that neural networks already have in consequence of training. LSTM were introduced by [14] and it aimed for a better performance by tackling the vanishing gradient issue that recurrent networks would suffer when dealing with long data sequences. It does so by keeping the error flow constant through special units called ”gates” which allows for weights adjustments as well as truncation of the gradient when its information is not necessary.

$$\frac{\sum_{i=t-n+1}^{t} \frac{C_i - C_{i-1}}{C_{i-1}}}{n}$$

The proposed system focuses on four parameters given below.

Price Fickle:

This is an average over the past n days of percent change in the given stock's price per day.

Price Strength

This is an average of the given stock's Strength over the past n days. Each day is labeled 1 if closing price that day is higher than the day before, and −1 if the price is lower than the day before.

$$\frac{\sum_{i=t-n+1}^{t} y}{n}$$

Zone Fickle

This is an average over the past n days of percent change in the index's price per day.

$$\frac{\sum_{i=t-n+1}^{t} \frac{I_i - I_{i-1}}{I_{i-1}}}{n}$$

Zone Strength

This is an average of the index's Strength over the past n days. Each day it is labeled 1 if closing price that day is higher than the day before, and −1 if the price is lower than the day before.

$$\frac{\sum_{i=t-n+1}^{t} d}{n}$$

Experiential Results

Step 1: This step is important for the download data from the net. We are predicting the financial market value of any stock. So that the share value up to the closing date are download from the site.

Step 2: In the next step the data value of any stock that can be converted into the CSV file (Comma Separate Value) so that it will easily load into the algorithm.

Step 3: In the next step in which GUI is open and when we click on the SVM button it will show the window from which we select the stock dataset value file.

Step 4: After selecting the stock dataset file from the folder it will show graph Stock before mapping and stock after mapping.

Step 5: The next step algorithm calculated the log2c and log2g value for minimizing error. So, it will predict the graph for the dataset value efficiently.

Step 6: In final step algorithm display the predicted value graph of select stock which shows the original value and predicted value of the stock.

Accuracy: We can compute the measure of accuracy from the measures of sensitivity and specificity as specified below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

	ES	PS
Accuracy	78%	91%

Table: 1 show the performance parameter

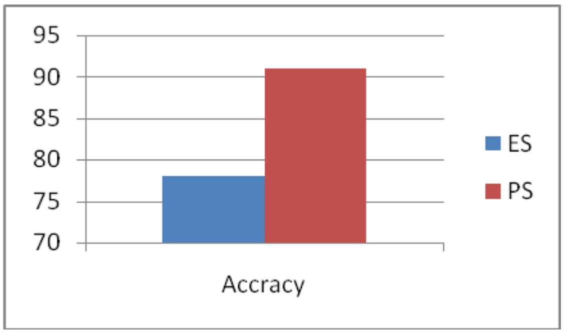

Figure: 1 graph representation for performance

Conclusion

In this paper, the enhanced recurrent neural network (ERNN) called Intelligent Term Memory (ITM). This analyze the daily stock markets prices and gives the accurate instructions to the customers. Machine learning methods were then tested on a wide range of data sources. The result of some models looked hopeful, but ultimately failed when they were put through realistic trading simulations. This highlights that the stock market is prone to differences between theory and practice.

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