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Financial Market Prediction Using Financial Data by Sentimental Analysis

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ABSTRACT: Predicting stock market prices has been a topic of interest among both analysts and researchers for a long time. Stock prices are hard to predict because of their high volatile nature which depends on diverse political and economic factors, change of leadership, investor sentiment, and many other factors. Predicting stock prices based on either historical data or textual information alone has proven to be insufficient. Existing studies in sentiment analysis have found that there is a strong correlation between the movement of stock prices and the publication of news articles. Several sentiment analyses studies have been attempted at various levels using algorithms such as support vector machines, naive Bayes regression, and deep learning. The accuracy of deep learning algorithms depends upon the amount of training data provided. However, the amount of textual data collected and analyzed during the past studies has been insufficient and thus has resulted in predictions with low accuracy. In our paper, we improve the accuracy of stock price predictions by gathering a large amount of time series data and analyzing it in relation to related news articles, using deep learning models. The dataset we have gathered includes daily stock prices for S&P500 companies for five years, along with more than 265,000 financial news articles related to these companies. Given the large size of the dataset, we use cloud computing as an invaluable resource for training prediction models and performing inference for a given stock in real time. Index Terms-stock market prediction, cloud, big data, machine learning, regression.

KEYWORDS: Companies, models, Data ,Feature extraction, Facebook, Recurrent neural networks, Stock markets

I. INTRODUCTION

It is a proven fact that investing in the stock market fetches more profits in the longer period of time but that is not always the case. Choosing which stock to invest in plays a crucial role in the profit to be obtained. Investing in a stock is nothing but committing our money to a particular company listed in the stock market, with an expectation of getting an optimized profit. A solid investment is not possible without a prior homework on the investor's part. A proper analyzation is an important step, before agreeing to invest on a particular stock. Randomly chosen stocks for investment can lead to adverse losses.

Many newbie investors today do not have any idea of how the future of the stock will look like. For them, it's more like a show of hands, invest in any randomly chosen stock, if its price goes up, lucky enough else better luck next time! In reality, it doesn't work that way. The astrology of predicting the future stock price is one of the most trending and debated topics of all times concerning to various fields which include statistics, finance, trading and computer science, its motivation unquestionably, to forecast the direction of the future stock price, so that they can be bought and then sold at greater profits.

The stock's price depends on many factors such as market forces, the relation between demand and supply etc. If the market demands a particular stock more than what is supplied, the price of the stock goes up; otherwise, the price goes down, i.e., when the supply is more than the demand. Most of the stock market investors are great believers too! Some believe that it's an impossible task to predict the stock price while some say; it is completely predictable given a little bit of graphical analysis and a few calculations from the past. While the latter kind of investors are very much right in their beliefs, practically, it's quite more than that.

The sentiments, attitude as well as the expectations of the people who invest in the stock, play an important role in the task of stock price prediction. Many people use the technical predictors to evaluate the performance of a company through a small time period. Most recently, the online media too has played a crucial role in the behaviour of the stock market. Evidence shows that the news articles published through the online media related to the companies have a greater impact on the future stock price. Even a tiny issue may result in a great impact on the people's money. Hence, by following the news articles regarding a particular financial set up over the available online media, the future stock price of that firm may be evaluated.

Again, due to exploding number of news articles that are to be digested in less span of time, such a tracking is not feasible if it is to be done manually. The exhilarating field of Computer Science offers the most effective solution to

the above problem. The task of stock price prediction can be accomplished by certain tools like Sentiment Analysis. Sentiment Analysis automatically gives the overall sentiment of the news articles in just some fraction of seconds. With the astonishing popularity of these methods, it makes the developments in the stock market trends visibly clearer and easily understandable, by giving decent yield with little or no effort! The stock market is all about dynamics, hence it is extremely important to accurately forecast further movements of the stock bids.
The three entities that explicitly or implicitly affect decision making with regard to investment in the stock market are, news articles related to the company, financial health of the company and stock price movements of that company after a sequence of events. All of these three key aspects have been taken up in the present work for providing supportive evidence of the correlation between the stock values and news articles, to establish a system that provides the overall financial health of a company and to build a system that would analyse and predict the variations in stock prices over a timeline, based on the sequence of events. To begin with, here are some statistics.
The Bombay Stock Exchange (BSE) was set up in India in 1875 and is situated in Mumbai. Wikipedia shows that Bombay Stock Exchange is ranked as the world's 10th largest stock market by the capitalization of the market being $1.7 trillion as of 23rd January 2015. The internet made its way to India in the early 90's, the use of which has increased exponentially over the years. The internet user-base in India stands third largest in the world, with over 243,198,922 users as of 2014.The stock markets introduced internet trading (online-trading) in February 2002[Source: Wikipedia].This data clearly shows that the users of the internet surely look for the stock market predictors in the news articles and the historic prices of the company they are interested in.

II. RELATED WORKS

In 2019, Zhong and Eake present a process to predict the daily return direction of a set of stocks. Deep neural networks (DNNs) and traditional ANNs are deployed over the entire preprocessed, but untransformed, dataset along with two datasets transformed via principal component analysis (PCA) to predict the daily direction of future stock market index returns. While controlling for overfitting, a pattern for the classification accuracy of the DNNs is detected and demonstrated as the number of the hidden layers increases gradually from 12 to 1000. Simulation results show that the DNNs using two PCA-represented datasets give significantly higher classification accuracy than those using the entire untransformed dataset or other hybrid machine learning algorithms. The trading strategies guided by the DNN classification processbased on PCA-represented data perform slightly better than the others tested, including a comparison against two standard benchmarks.

In 2018, Pierdzioch and Risse use a ML algorithm known as boosted regression trees (BRT) to implement an orthogonality test of the rationality of aggregate stock market forecasts. The BRT algorithm endogenously selects the predictor variables used to proxy the information set of forecasters so as to maximize the predictive power for the forecast error. The BRT algorithm also accounts for a potential non-linear dependence of the forecast error on the predictor variables and for interdependencies between the predictor variables. Their main finding is that, given the set of predictor variables used in this study, the rational expectations hypothesis (REH) cannot be rejected for short-term forecasts and that there is evidence against the REH for longer term forecasts. Results for three different groups of forecasters corroborate the main finding.

In 2017, Chong, Han and Park analyse deep learning networks for stock market analysis and prediction. Deep learning networks extract features from a large set of raw data without relying on prior knowledge of predictors which makes it useful for high frequency stock market prediction. They provide an objective assessment of both the advantages and drawbacks of deep learning algorithms for stock market analysis and prediction. Using high-frequency intraday stock returns as input data, they examine the effects of three unsupervised feature extraction methods—principal component analysis, autoencoder, and the restricted Boltzmann machine—on the network's overall ability to predict future market behaviour.

In 2016, Li et. al. presents the design and architecture for a trading signal mining platform that employs an extreme learning machine (ELM) to make stock price predictions based on two data sources concurrently. Experimental comparisons between ELM and support vector machines and backpropagation neural networks (BPNNs) are made based on the intra-day data of the H-share market (shares of companies incorporated in mainland China that are traded on the Hong Kong Stock Exchange) and contemporaneous news archives. The results show that (1) both RBF ELM and RBF SVM achieve higher prediction accuracy and faster prediction speed than BPNN, (2) the RBF ELM achieves similar accuracy with the RBF SVM, and (3) the RBF ELM has faster prediction speed than the RBF SVM.

In 2016, Dash and Dash introduce a novel decision support system using a computationally efficient functional link artificial neural network (CEFLANN) and a rule set to more effectively generate trading decisions. They view the stock trading decision as a classification problem with three possible values –buy, hold or sell. The CEFLANN network usedin the decision support system produces a set of continuous trading signals by analyzing the nonlinear relationship that exists between some popular technical indicators. The output trading signals are also used to track trends and to produce trading decisions based on that trend using trading rules. This is a novel approach focused on profitable stock trading decisions through integration of the learning ability of the CEFLANN neural network with the technical analysis rules. The model is compared against other machine learning techniques such as a SVM, a naive Bayesian model, a K nearest neighbor model, and a decision tree.

In 2015, Patel, Shah, Thakkar and Kotecha compares four Indian stock market prediction models: ANN, SVM, random forest, and naive-Bayeswith two approaches for model input. The first approach for input data involves computation of ten technical parameters using stock trading data (open, high, low and close prices), while the second approach focuses on representing these technical parameters as trend deterministic data. They assess the accuracy of each of the prediction models for each of the two input approaches. The experimental results suggest that, for the first input data approach, random forest outperforms the other three prediction models. They also find that the performance of all of the prediction models improves when these technical parameters are represented as trend deterministic data.

In 2013, Chavan and Patil contribute to our understanding of ANN stock market prediction by surveying different model input parameters found in nine published articles. They attempt to find the most important input parameters that produce better model prediction accuracy. Based on their survey, they find that most ML techniques make use of technical variables instead of fundamental variables for a particular stock price prediction, while microeconomic variables are mostly used to predict stock market index values. In addition, hybridized parameters produce better results when compared with the use of only a single input variable type.

In 2012, Dai, Wu and Lu, a time series prediction model that combines nonlinear independent component analysis (NLICA) and neural networks is proposed for forecasting Asian stock markets. NLICA is a novel feature extraction technique to find independent sources from observed nonlinear mixture data where no relevant data mixing mechanisms are available. In the proposed method, they first use NLICA to transform the input space composed of original time series data into the feature space consisting of independent components representing underlying information from the original data. Then, the independent components are used as the input variables for the neural network to build the prediction model.

In 2011, Guresen, Kavakutlu and Daim A number of neural network models and hybrid models have been proposed in an attempt to outperform traditional linear and nonlinear approaches for stock market forecasting, but there are some limitations in most ANN model performance in this domain. Evaluate the effectiveness of a multi-layer perceptron (MLP), a dynamic artificial neural network (DAN2), and hybrid neural networks which use generalized autoregressive conditional heteroscedasticity (GARCH) to extract new input variables.

In 2011, Yeh, Huang and Lee in this research address problems that arise when using support vector regression to forecast stock market values when dealing with kernel function hyperparameters. Typically, a hyperparameter is a parameter whose value is set before the learning process begins. In their system, advantages from different hyperparameter settings can be combined and overall system performance can be improved. They develop a two-stage multiple-kernel learning algorithm by incorporating sequential minimal optimization and the gradient projection method. Experimental results using datasets taken from the Taiwan Capitalization Weighted Stock Index show that the modified method performs better than other methods.

The objective for this study is to identify directions for future machine learning stock market prediction research based upon a review of current literature. Given the ML-related systems, problem contexts, and findings described in each selected article, and the taxonomy categories presented earlier, several conclusions can be made about our current knowledge in this research area. First, there is a strong link between ML methods and the prediction problems they are associated with. This is analogous to task-technology fit where system performance is determined by the appropriate match between tasks and technologies. Artificial neural networks are best used for predicting numerical stock market index values. Support vector machines best fit classification problems such as determining whether the overall stock market index is forecast to rise or fall. Genetic algorithms use an evolutionary problem-solving approach to identify higher quality system inputs, or predict which stocks to include in a portfolio, to produce the best returns. While each study did illustrate that the methods can be effectively applied, the single method applications do have limitations. Hybrid machine learning techniques are one solution that can mitigate

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some of these limitations. The problem is that, at some point, the systems become so complex that they are not useful in practice. This is a theoretical and practical problem that can be addressed in future studies..

III. METHODOLOGY OF PROPOSED FRAMEWORK

The overall process of predicting the direction of the stock market consists of various steps which include data collection, text pre-processing and feature selection. In order to carry out the overall research the programming is needed. R language, python, Java was used. The packages of those tools were used to implement the proposed algorithms.
The data needed for our problem is of two types. The historical stock prices and the news articles from which the sentiments are to be extracted. In contrast to the other systems, which used the static data, our system is based on the streaming data as well as the static data. The crawler crawls on the specified website and extract the news articles of the specified company for which the future direction of the stock is to be predicted. Since the stock prices have to be correlated with the news articles, the news articles have to be extracted along with the timestamps. These news articles are then served as the input to the sentiment analysis module.
Since many years, the researchers have been exploring avenues in sentiment analysis and they came up with many different algorithms for the classification of sentiment of the text. Every algorithm has some advantages and drawbacks. The choice of the algorithm for sentiment analysis may depend on the available datasets, domain and prior experience. Among the approaches, linguistic based, lexicon based and machine learning, one approach is to be chosen. After choosing the approach, one has to decide the appropriate algorithm in that approach.

In the first module Neural Network Predictor, the artificial neural network has been used which takes the inputs of historical stock prices and the sentiment score of the news articles and produces the predicted prices.

The following Figure 4.1 shows work flow in the module neural network predictor.

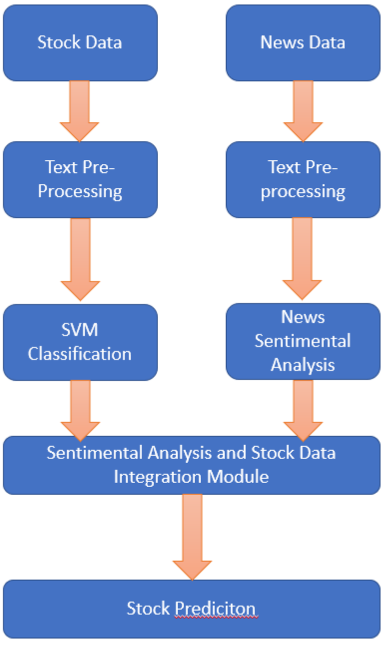

Figure 4.1: Work flow of Stock Price Predictor module

The module, combined technical and sentiment analysis exploits the advantages of both technical analysis and sentiment analysis and gives the overall health of a company. This gives the investor, an informed decision over, whether or not to invest in the company under consideration. The following figure Fig. shows the work flow in the module combined technical and sentimental analysis.

A.TEXT PREPROCESSING

The accuracy of Sentiment Analysis can be improved by choosing the appropriate data pre-processing technique. This fact makes the data pre-processing step very crucial. Some of the news articles need specific pre-processing techniques apart from the standard pre-processing techniques since the content generated by the user community for example Twitter generated messages. Data pre-processing reduces the word space significantly, but there are chances of the loss of information also.

The steps involved in data pre-processing are:

i. Tokenization: A basic strategy could be to split the news articles into all nonalphanumeric characters. There may be a chance of information being lost, advanced techniques are needed for text tokenization. This step would be domain dependent.
ii. Dropping of the words which are common: A word which has no or little information value, that is common, can be identified (For eg: an,is,be and in etc.). The text space would be reduced significantly and only the data which contribute most for the sentiment identification remains in the text.
iii. Normalization: It is a process of creating the terms' equivalence classes. Example INFOSYSS and INFY.
iv. Lemmatization and Stemming: News articles may have different word forms.

B.SENTIMENT ANALYSIS ALGORITHM

After the news articles are extracted the next step is to extract the sentiment which gives an overall opinion of whether that article is negative, positive or neutral. The sentiment analysis algorithm attempts to identify the opinion/sentiment that a news article may hold towards a financial company.
As shown in the Figure 4.2 the steps involved in Sentimental analysis are:

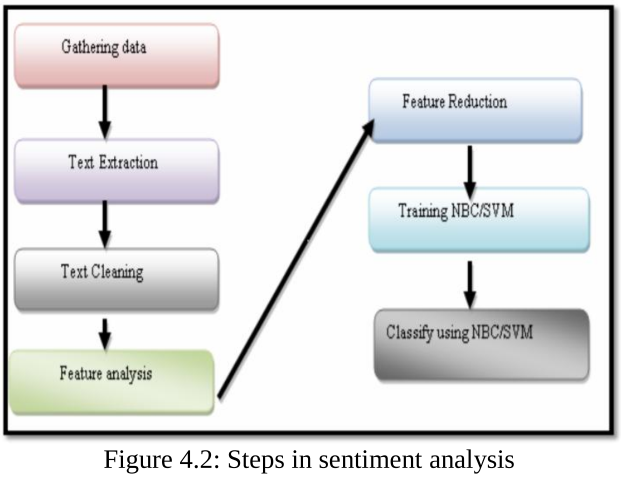

Figure 4.2: Steps in sentiment analysis

Step 1: Gathering data from internet is solely based on the (SOR) Subject of Reference (e.g. ICICI bank). We use web mining techniques (ex. crawler) to gather all web pages where the SOR is mentioned.
Step 2: Text Extraction can be done using several data mining or text mining techniques starting from simple 'keyword matching' to 'DOM structure mining' to 'neural networks' methods. The major challenge here is that web documents are highly unstructured and no single method can give 100% clean text extraction for all documents.
Step 3: Text Cleaning is mostly heuristic based and case specific. By this what we mean is to identify the unwanted portions in the extracted contents from Step 2 with respect to different kinds of web documents (e.g. News article, Blogs, Review, Micro Blogs etc.) and then write simple clean-up codes based on that learning, which will remove such unwanted portions with high accuracy.
Step 4: Once we have the data corpus of clean documents from the previous steps, it is then put to the various knowledge processing engines. This data can be analysed for feature analysis or business analytics or market research or consumer buzz trends or consumer sentiment analysis etc. depending on the need. Various techniques are used for each such purpose. For example, Inverse Document Frequency (TF-IDF) technique can be used to gather a pool of various features for the SOR, which in case of ICICI bank can get a pool as customer service, credit card, recovery agent, customer satisfaction etc. This is called feature analysis. From this pool one can determine things like how many consumers talk about recovery agent while talking about credit cards compared to how many consumers talk about customer satisfaction while talking about credit cards.
Step 4.1: Obviously, the above technique for Feature analysis will throw up few unwanted features in the pool which need to be removed from final analysis. This can be done by feature mapping from pool with keywords representing the variouswell-known features. These features can also be pre-defined by the SOR.

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Step 5: Sentiment Analysis is done on the document to categorize as Positive, Negative or Neutral. Sentiment analysis can be done on the clean extracted web documents in two manners - manual rating or automated rating of such web documents. While manual rating is a near perfect method to do it, but it is a slow process when the volume of web documents is too high. Whereas automated system will be much faster method, but is bound to lack accuracy since it is effectively machine learning and deriving human sentiments through user generated content. Also, the language barrier is a major challenge for automated sentiment analysis. Nevertheless, extensive research work on Natural Language Processing has addressed such challenges well and reasonably high-performance machine learning techniques have evolved which can do sentiment analysis of web documents. The most efficient techniques are Naive Bayesian Classifier (NBC) and Support Vector Machines (SVM)Maximum Entropy. Apart from these the lexicon-based techniques are also available. These learning algorithms require a learning corpus to first train on then from that training it can derive sentiment from web documents.
Step 5.1: Training NBC/SVM is fairly straightforward and well-studied technique, in which, a manually rated corpus of several thousands of web documents is generated, categorizing them as negative, positive or neutral for a given SOR. These corpuses then fed to the NBC/SVM engines which generate several measuring parameters for a given document to fall into one of the three categories [negative, positive or neutral].
Step 5.2: Once the NBC/SVM engines are trained, they can now be used to categorize rest of the web documents using the parameters generated by them. The accuracy definitely won't be 100% but several layers of training and tuning can increase and optimize the accuracy. Once the sentiment is extracted these values would be combined with the historical values and the direction of the stock market is predicted. The techniques like Artificial Neural Networks and NBC are used for the prediction purposes, as mentioned already. The artificial neural network uses five input neurons, two hidden layers and one output neuron. The historical prices and the sentiment score are the inputs to the system and the network learns from the training. It produces the next day price based on the input historical stock values and sentiment score. In NBC, based on the probability of features, the classifier is trained and the classification of news articles as positive, negative or neutral is learnt.

IV.RESULTS

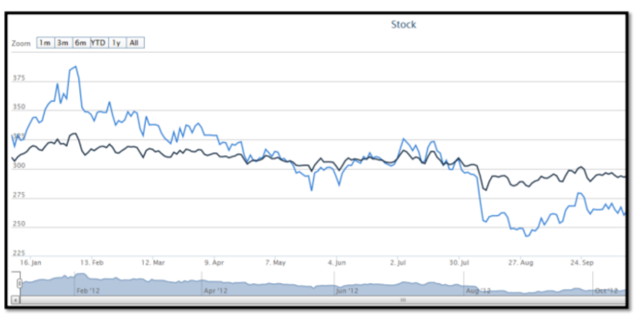

Figure 5.2: Plotting of Stock values for AIRTEL

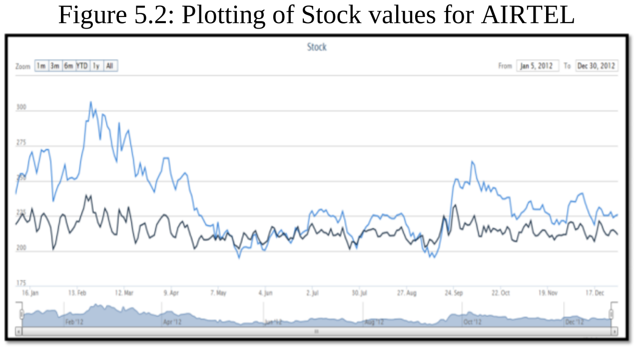

Figure 5.3: Plotting of Stock values for BHEL

Experiment Analysis

$$Precision = \frac{Number\ of\ correct\ positive\ predictions}{Number\ of\ positive\ predictions}$$

$$F1\ Score = \frac{2 * Recall * Precision}{Recall + Precision}$$

$$Recall = \frac{Number\ of\ correct\ positive\ predictions}{Number\ of\ positive\ examples}$$

Table5.4: Comparison of classifiers

	Precision	Recall	F1 Sore	Accuracy
SVM	71.34%	72.11%	71.23%	74.3%
Auto Regressive Model	86.5%	85.3%	85.11%	87.6%
boosted regression trees	89.3%	88.8%	89.4%	90.34%
hybrid machine learning algorithms (ANN/DNN)	91.8%	90.3%	91.2%	92.5%
Proposed Model	95.5%	94.2%	95.3%	96.9%

V.CONCLUSION

In the experiment conducted to achieve the third objective only the companies with the negative news have been selected, and the results proved that there is fall in the stock price of that company immediately after the negative news. It shows the increase in tendency again after an event takes place. Empirical evidence from the work done in this thesis would provide informed decision to the investor so that he could safely invest in a company and get high yielding. The novel sentiment analysis methods adopted in our work have been successfully adopted in achieving our three objectives, which can be applicable to real life scenario.

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