EMPLOYABILITY OF NEURAL NETWORK ALGORITHMS IN PREDICTION OF STOCK MARKET BASED ON SENTIMENT ANALYSIS

Pranjal Bajaria

Student, Bal Bharti Public School, Dwarka, Delhi

ABSTRACT

Expansion of verbal technologies and saturation of communal mass media offers prevailing possibilities to research users' thinking and emotional states of individuals. Amid this paper, wemention the risk to enhance a stock exchange indicators prediction's accuracy by mistreatment information concerning mental states of Twitterati. For the investigation of mentalsituations, we tend to usethe lexicon-based approach, which permitstheNorth American nation to gaugethe presence of eight common emotions in additionto 755 million tweets. Neural Networks algorithms and SVM to forecast DJIA and S&P500 indicators are mentioned.

***Prediction**; stock market indicator; Twitter; mood; psychological states; Support Vector Machines; Neural Networks*

I. INTRODUCTION

Machine learning algorithms have been used in the stock market for forecasting for a long time [1], [2]. The most common methods areSupport Vector Machinesand Neural Networks[1], [3]. Usually, machine learning algorithms trained on technical data about stock movements, for example moving averages. Although, technical data is important for stock prediction contemporary traders need more advanced strategies to outperform the market. According to behavioral economics, it could be useful to add information regarding psychological states of people including moods [4].

In the most recent year's critical advancement was exhibited in utilizing Twitter as an extra wellspring of data [5], [6]. Bollen et al. (2011) announced that the investigation of the content substance of day by day Twitter channels expanded exactly to DJIA predictions up to 87.6%. It worth to mention, despitethe wide time range of available data the prediction'saccuracy,was measured only for 19 days. Bollen and his fellows wrote: "February 28, 2008, to November 28, 2008, is chosen as the longest possible training period while Dec 1 to Dec 19, 2008, was chosen as the test" [1, p.5]

Z, Fuehres , and Gloor (2001) studied Twitter tweets to forecast stock market such as DJIA,VIX, S&P500, NASDAQand originate a high destructiveconnection (0.726, significant at $p<0.01$) among Dow Jones index and occurrence of disputes “hope”, “fear”, “worry” in tweets [7].

Lazer and Chenvalidated that, the proposedapproach by Mao, Bollen,and Zeng, creating a more cost-effective trading tactic, but their research does not reveal the prediction’s accuracy [2]. Althoughon April 23rd hackers’ attack onAssociated Press Twitter account showed that analysis of news is widely used in trading [8], we could not found such strong evidence for sentiment analysis techniques. The first challenge to implementopinion mining on data was completed by a vergedepositnaming Derwent Capital Markets, nonetheless, their output did not perform any productivity [9]. Afterward, the stock was changed to DCM Capital and presented to retail investors opinion mining-based trading framework [9]. Although, a nextchallenge was not beneficialand the opinion mining-based frameworkwas put up for sale in an auction by CEO Paul Hawtin.

Chief of Asset Management and Financial Technology said that few supports purchase investigations of Twitter and other online networking from Gnip to be the primary who can get moves in slant as the way to profiting by the market's wild swings [10].

II. METHODOLOGY

In thisstudy, we come across with two main tasks: opinion miningstudy and forecasting of stock market constructedon opinion mining information.

A. Opinion Mining Analysis

Research in NLP provides many directions for sentiment analysis, 1st is classification supported human developed gold commonplace [11]. All classes of sentiments ought to be bestowed in gold stock, therefore it may won’ttrain Naïve mathematician or alternative machine learning calculations for studying alternative twitter posts [12]. It developmentstandard is typically related to piles of labors and effort of a squad of semantics (e.g. Lyashevskaya et al. [13]).

The nextmethod relies on thesauri. This approach was utilized by Bollen and his coworkers, United Nations agency has received the simplest results to the present moment, and that we determined to follow them in selecting a wordbook approach for sentiment analysis [4]. In its modest type, this method was utilized by Gloor, Zhang, and Fuehres by analyzing the abundance of tweets having words “hope”, “fear” and “worry” [7].

In our research, we tend to understand two versions of lexicon-based approach. First, we tend to merely calculate occurrences of words “hope”, “worry” and “fear” in twitter tweets. Second, we tend to produce a lot of advanced dictionaries for every of eight basic emotions and analyze the presence of those words. to research the potency of recognition of emotions we tend to raise consultants in linguistics to form gold-standard for emotions in tweets. to examine the quality of emotions recognition we tend to used commonplace measures recall, exactness and F-measure [12].

A. Stock Market Prediction Using Machine Learning

In our theory,two machine learning algorithms have been used, allowing us to organizeeras by the appearance of occasions and use generatedideal for forecasting. They are Support Vectors Machines and Neural Networks.

Learning technique on 3 sets of knowledge. the primary set of knowledge were the features of the stock exchange in earlier days, we tend to decide it simple set (Basic). we tend to suppose that the judgment between the accuracy of predictions supported our 3 learning sets are completely different. in line with our hypothesis concerning the presence of extra data on Twitter, we tend to expect that the primary set can offer lowest accuracy level, second provides a higher accuracy and therefore the utmost level of forecasting accuracy are received supported the usage information set Basic&8EMO.

Bollen and his co-authors, in their work,initiated higher predictions supported information that occurs throughout three to four earlier shift within the DJIA [4]. to check these findings, data from Twitter was accustomed to training Support Vector Machine and Neural Network algorithms with the time lag from one day to one week.

B. Data description

Twitter API has been used to download tweets from Twitter with downloads approximately of 145 000 tweets in sixty minutes.We made use of the yahoo finance website (http://finance.yahoo.com), which gives opening and closing prices along with thequantity for all trade days.

The day period from 1/02/2016 till 29/04/2016 was divided. In the first 60 days, machine learning calculations were trained, and then trained algorithm makes a prediction for last 61st day. We can use only data from work days and after division, we received 80 periods (every period consists from 61 days).

For lagged analysis we shift data, that is why the number of experiments varies a little from 76 to 80 inrespecttothe time lag.

III. ANALYSIS

A. Sentiment analysis

For Opinion mining analysis we tend to set to use the lexicon approach, first of all as a result of it will offer reliable info, and second as a result of it needs rarerassets to run and might be a lot of quicker than wide used Naïve Bayes formula. we tend to use a short Mood Reflection Scale with eight scales and a pair of adjectives representing every mood state for start line in the creation of dictionaries [14]. we tend to additionally superimpose all synonyms of designated adjectives from the WordNet lexicon [15].

To test the correctness of the emotion analysis of our formula we manually create a gold standard out of 240 tweets, thirty per sentiment class. Each oneof the 240 tweets was analyzed by a translator with a specialdegree in West Germanic language and separated to at least one or many emotions classes (it additionally might happen that the tweet doesn't have any emotional info, which means that tweet had a zero score on all eight scales). the primary version of dictionaries gave a decent result on the take a look at knowledge, however, the study of mistakes doesn't permit the United States of America to improve our calculations by adding neweradjectivesor to acknowledge spinoff words like “happyyy” or “happpppppyyyyyyy”. Better results for all parameters of the potency of sentiment analysis are provided by the second version of the form which consists of 217 words.

	First version			Second version		
	Precision	*Recall*	*F-measure*	*Precision*	*Recall*	*F-measure*
Happy	87%	87%	87%	90%	93%	92%
Loving	77%	77%	77%	84%	87%	85%
Calm	63%	40%	49%	71%	57%	63%
energetic	57%	57%	57%	63%	63%	63%
Fearful	61%	57%	59%	70%	70%	70%
Angry	70%	63%	67%	79%	77%	78%
Tired	69%	67%	68%	79%	73%	76%
Sad	85%	73%	79%	89%	80%	84%

A. Stock Market Growth Forecasting

We began by creating informational indexes. To start with, we separated tweets just from work days, then composed a Java-content to produce the informational indexes Basic, Basic&WHF, Basic&8EMO. Every datum set had 7 sub tables for slack in time from one day to one week. To apply Support Vector Machine, and Neural Networks calculations we partitioned the days into two gatherings by including a variable development (0,1).

We divided the analyzed period intodatasets contained 61 days. Using the first 60 days as a training sample and 1 day as a testing sample. Analyzed period permitted us to conduct more than 70 prediction experiments.

Results presented in Table 3 demonstrate that using more complex approach to extract emotional states do not furnish more information than basic method rely on appearance of the words “worry”, “fear” and “hope”. Although, Twitter analysis add some information we could not say that quality of forecast changes significantly. The higher accuracy demonstrated by Basic&Emo data set is equal to 61.10% (time lag 2), for Basic&WHF is equal to 61.84% (time lag=1), difference is not significant (z2(df=1)= 0.084, p= 0.771).

IV. DISCUSSION

The utilization ofTwitter information for securities exchange forecast resembles an endeavor to utilize an enchantment precious stone ball or inconsequential information. In any case, it might not be as implausible as it shows up at first sight. In light of the study by Bollen and his partners, we needed to repeat and grow their outcomes in a wide time allotment. Use of estimation examination information for machine learning calculations enables us to get the most extreme exactness of securities exchange expectations for DJIA – 64.10%. For DJIA.our accuracy lies less than 87.6% of that calculated by Bollen and co-authors. This could lead to a deduction that probably higher prediction rate demonstrated by Bollen and co-authors was courtesy of a small test period (19 days).

These results could also be explained by othercircumstances. First, it might be that information about the use of Twitter for DJIA become available to trading society in 2010 and now this analysis technique could not consistently beat the market as some of the traders already used it. Partially this could confirm the efficient market hypothesis. Second, probably we need to extend the training period from 60 days to several monthsas Bollen did. Third, we were not able to compare performance directly because proprietary nature their algorithm and further improvement of our sentiment analyzer needed.

However, we found out that Support Vector Machine provides a little better prediction accuracy of S&P500 indicator (62.03%) than 51.88% demonstrated by Ding et al. [3].

We found that our Twitter analyzer could give the altogether higher precision of forecast and couldn't affirm our speculation, as we found no noteworthy contrasts in normal exactness of expectations dependent on every one of the three informational indexes.

Our examination gives another contention about a potential shot of enhancing prediction of securities exchange pointers utilizing human assessments investigation. In spite of the fact that, we think it is too soon to estimate that Twitter assessment examination couldn't enhance conjectures and all the more testing is required. Likewise as Twitter is developing quickly it very well may be seen that further trials will require more exertion: in 2008, 9,853,498 tweets could speak to the period from February 28 to December nineteenth, 2008, and in 2013 for speaking to period from 13 February until 29 September 2013 we should take a gander at 755'000 101 tweets. Considering distinctive length eleven months in research of Bollen et al. also, eight months in our own, we could gauge that to make an entire year examination we need to download and investigate in excess of one billion of tweets.

V. CONCLUSION

In our research, we tested the hypothesis that sentiment analysis of Twitter data could provide additional information and this could increase the accuracy of stock market prediction.

We made server application and in the period from 13/02/2013 till 29/09/2013 downloaded 755'000 101 tweets. Following stage was the formation of quick and dependable calculation for notion investigation. To achieve it we utilized a vocabulary based methodology and the second form of lexicons demonstrated tasteful execution.

Our preliminary results indicate that the addition of information from Twitter does not allow us to significantly increase accuracy. The best average accuracy rate 64.10% was achieved using a Support Vector Machine algorithm to predict DJIA indicator.

We plan to increase the trainingperiod and improve our sentiment analysis algorithms in further research.