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Nifty Auto Index prediction on the basis of tweets sentiments

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***Abstract*— In this paper we investigate the complex relationship between tweet sentiments with the Nifty Stock market Auto Index (esp. stock prices). We will analyze sentiments for nearly 1 million tweets from December 2015 to March 2016 for Nifty Auto Index which includes 15 auto industries stocks. Our results will show high correlation between stock prices and twitter sentiments. A Granger causality analysis and a Neural Network are then used to investigate the hypothesis that public mood states are predictive of changes in Nifty Auto Index closing values.**

Keywords- Stock market; sentiment analysis; Twitter; Micro blogging; social network analysis

I. Introduction

Twitter is very popular micro blogging website, where users can update their status in tweets, follow the people they are interested, re-tweet others' posts and even communicate with them directly. Since it launched in 2006, its user base has been growing exponentially. As of May 2016, Twitter has more than 500 million users [24]. Recently, Twitter's popularity has drawn more and more attention of researchers from different disciplines. There are several streams of research investigating the role of Twitter. Besides the general understanding of Twitter, other researchers are interested in its prediction power and potential application to other areas like movies box office collection, political election results and stock market prediction.

In this paper, we describe work to predict NIFTY Auto Index by analyzing Twitter posts sentiments. There is not much research on prediction of Indian Stock Market on the basis of Web Buzz. Since Stock market is a volatile entity, we have zero down our research between whole market index predictions to single stock value prediction. Thus we have used NIFTY Auto Index High values to predict a day before on the basis of Twitter users' tweets sentiments (positive or negative) along with High, Low, Opening and Closing values of same index for last 4 days. We have also used Granger Causality analysis as linear regression tool to confirm that we can predict the values and Neural network as nonlinear tool to actually predict the next day value of NIFTY Auto index.

II. Literature Review

In the last two and half decades forecasting of stock returns has become an important field of research. Previously researchers had attempted to establish a linear relationship between the input economic variables and the stock returns. But with the discovery of nonlinearity in the stock market index returns (A.Abhyankar et al. [10]), there has been a great flow of researchers towards the nonlinear prediction of the stock returns. Most of them required that the nonlinear model be specified before the stock estimation is done. But since the stock market return is being uncertain, chaotic, noisy and nonlinear in nature, ANN has gaining more acceptance as better technique for capturing the structural relationship between a stock's performance and its determinant factors (Refenes et al.[11], S.I. Wu et al.[12], Schoeneburg, E.[13],) In literature, different sets of input variables are used to predict stock returns or the same set of stock return data. Some researchers used input data from a single time series where others used heterogeneous market information and macroeconomic variables. Some researchers even preprocessed like normalization, these input data sets before feeding it to the ANN for forecasting.

Other prominent literatures are that of Siekmann [14] who implemented a network structure using fuzzy rules that contains the adaptable fuzzy parameters in the weights of the connections between the first and second hidden layers.Kim and Han [16] used a genetic algorithm to transform continuous input values into discrete ones. The genetic algorithm was used to reduce the complexity of the feature space.

Kishikawa and Tokinaga [15] used a wavelet transform to extract the short-term feature of stock trends.Kim and Han [16] used neural network modified by Genetic Algorithm. Kim and Chun (1998) used refined probabilistic NN (PNN) to predict a stock market index. Pantazopoulos et al. [17] presented a neuro fuzzy approach for predicting the prices of IBM stock.

Some literatures are also available in Indian context. Panda, C. and Narasimhan, V.[19] used the ANN to forecast the daily returns of Bombay Stock Exchange (BSE) Sensitive Index (Sensex). They reported excellent performance of neural network than linear autoregressive and random walk models for forecasting of daily BSE Sensex returns.

The previous studies have used various forecasting techniques in order to predict the stock market trends. Some attempted to forecast the daily returns where others developed forecasting models to predict the rate of returns of individual stocks. In many papers it was also found that researchers have attempted to compare their results with other statistical tools. And these findings provide strong motivation for modeling forecasting tools for stock market prediction. The uniqueness of the research comes from the fact that the research employs a neural network based forecasting approach on Nifty Auto Index. Furthermore, as not much work has been done on the forecasting of Indian stock market indices using neural network, this paper will actually help to understand the microstructure of Indian market.

III. Data Collection Methodology for Tweets and NIFTY Auto Index

In this section we describe our method of Twitter tweets and NIFTY Auto Index data collection.

A. *Tweets Collection and Processing*

We obtained a collection of public tweets that was recorded from December 10, 2015 to March 10, 2016 (9,853,498 tweets posted by pre-define users) using the public API. For each tweet these records provide a tweet identifier, the date-time of the submission, its submission type, and the text content of the Tweet which is by design limited to 140 characters. After removal of stop-words and punctuation, we group all tweets that were submitted on the same date. We only take into account tweets that match the expressions "I feel","i am feeling","i'm feeling","i dont feel", "I'm", "Im", "I am", and "makes me". In order to avoid spam messages and other information-oriented tweets, we also filter out tweets that match the regular expressions "http:" or www.

We have identified following Hashtags which are related to 15 companies which are listed in Auto Index. Table (1) shows the corresponding company name and Hashtags related to it.

Company Name	HashTags
Amara Raja Batteries Ltd.	#amarajabat,
Apollo Tyres Ltd.	#ApolloTyres #APOLLOTYRE
Ashok Leyland Ltd.	#ashokleyland #ashokley
Bajaj Auto Ltd.	#bajajauto #BajajAutoLtd #Bajaj #bajajavenger
Bharat Forge Ltd.	#bharatforg #bharatforgeltd
Bosch Ltd.	#bosch
Eicher Motors Ltd.	#eicher #eichermotors #Royal #Enfield #Motorcycles
Exide Industries Ltd.	#exideind
Hero MotoCorp Ltd.	#motocorp #heromotoco #hero_motocorp #heroduet
MRF Ltd.	#mrf #mrfs
Mahindra & Mahindra Ltd.	#mahindratractors #Mahindra #MahindraRise
Maruti Suzuki India Ltd.	#marutisuzukiindia #suzuki_india #marutis #marutisuzu
Motherson Sumi Systems Ltd.	#mothersumi #skiet
TVS Motor Company Ltd.	#tvsmotor #tvs_motor_company #tvs
Tata Motors Ltd.	#tatamotors #tata #TataMotorsLtd

Table (1): Auto Company Hashtags

We have also decided to look for following users tweets only and they are most influential trading tweeter users. The Table (2) shows the list of tweeter users used for fetching their tweets on the basis of above HashTags.

livemint	invest_mutual	binduananth
elearnmarkets	WSJ	ajit_ranade
ReutersIndia	NagpalManoj	Moneylifers
EconomicTimes	menakadoshi	deepakshenoy
andymukherjee70	alokgbc	_anujsinghal
NDTVProfit	mohitsatyanand	fayedsouza
forbes_india	monikahalan	dugalira
moneycontrolcom	nachiketmor	jayantsinha
Anil_Tulsiram	arunjaitley	arvindsubraman
ETNOWlive	nsitharaman	kaushikcbasu
ETmarkets	pjain	kayezad
Investopedia	paragparikh	Latha_Venkatesh
BloombergTVInd	porinju	VetriSmv
shankarbhatt	shefalianand	shyamsek
AswathDamodaran	BMTheEquityDesk	bibekdebroy
CNBCTV18Live	cafemutual	Vijay_Pahwa
BT_India	RMantri	safalniveshak
SubirGokarn	sonias24	suchetadalal
ZeeBusiness	RajeevThakkar	kaul_vivek
FinancialXpress	RajivKumar1	bikeindia
NSEIndia	SadiqueNeelgund	india_auto
TOIBusiness	Iamsamirarora	motortrendindia
IIFL_Live	sandipsabharwal	carindia
RBI_Official	Sanjay__Bakshi	indiancarsbikes
surjitbhalla	udaykotak	autocarsindia
tejus_sawjiani	udaytharar	car_trade
carexpertsindia	burnyourfuel	carblogindia
indiacarnews	SureshSadagopan	theautomotive

Table (2) Twitter Users list

B. *NIFTY Auto Index Data Collection*

The NIFTY Auto Index Data for the given date range is collected from [25]. This sites stores all the related data for

Auto Index data viz. Opening value, Closing value, High Value and Lower value etc. The data thus downloaded will be used as input for both the analysis.

C. *Actual Data processing of Twitter tweets and NIFTY Auto Index Data*

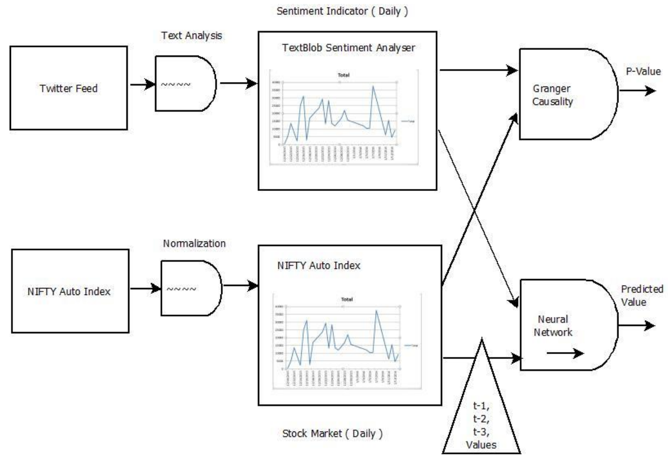

Fig. 1. Diagram outlining 3 phases of methodology and corresponding data sets: (1) creation and validation of TextBlob public mood time series from December 10, 2015 to March 10,2016 (Rail Budget, Annual Budget), (2) use of Granger causality analysis to determine correlation between NIFTY Auto Index, TextBlob public mood from December 10, 2015 to March 10,2016, and (3) training of a Neural Network to predict NIFTY Auto Index values on the basis of various combinations of past NIFTY Auto Index values and TextBlob public mood data from December 10,2015 to March 10,2016

As shown in Fig. 1 we proceed in three phases. In the first phase, we subject the collections of daily tweets to mood assessment tool TextBlob which measures positive vs. negative mood from text content. This result in a total of 2 public mood time series each is representing a potentially different aspect of the public's mood on a given day. In addition, we extract a time series of daily NIFTY Auto Index Opening/High/Low/Closing-values from [25]. In the second phase, we investigate the hypothesis that public mood as measured by TextBlob is predictive of future NIFTY Auto Index values. We use a Granger causality analysis in which we correlate NIFTY Auto Index values to TextBlob values of the past n days. In the third phase, we deploy a Neural Network model to test the hypothesis that the prediction accuracy of NIFTY Auto Index prediction models can be improved by including measurements of public mood. We are not interested in proposing an optimal NIFTY Auto Index prediction model, but to assess the effects of including public mood information on the accuracy of a "baseline" prediction model.

D. *Generating public mood time series for sentiment analysiss*

TextBlob is a publicly available Python package for sentiment analysis that can be applied to determine sentence-level subjectivity [21], i.e. to identify the emotional polarity (positive or negative) of sentences. It has been successfully used to analyze the emotional content of large collections of tweets [22] by using the OF lexicon to determine the ratio of positive versus negative tweets on a given day. To enable the comparison of TextBlob time series with actual values, we normalize them to z-scores on the basis of a local mean and standard deviation within a sliding window of k days before and after the particular date. For example, the z-score of time series Xt, denoted ZXt , is defined as:

ZXt = (Xt – Mean(Xt+k))/SD(Xt+k) ------------- Eq(1)

Where Mean(Xt+k) and SD(Xt+k) represent the mean and standard deviation of the time series within the period [t-k; t+k].This normalization causes all-time series to fluctuate around a zero mean and be expressed on a scale of 1 standard deviation.

IV. STATISTICAL ANALYSIS OF TWEETS SENTIMENT AND NIFTY AUTO INDEX VALUES

We begin our study by identifying the correlation between the Twitter feed features and NIFTY Auto index which give the encouraging values of statistically significant relationships with respect to individual company stocks(indices).

A. *Cross-validating Tweets sentiment against large socio-cultural events*

We first validate the ability of TextBlob to capture various aspects of public mood. To do so we apply them to tweets posted in a 3-month period from December 10, 2015 to March 10th, 2016. This period was chosen specifically because it includes several socio-cultural events that may have had a unique, significant and complex effect on public mood namely the Rail Budget (February 20, 2016) and Annual Budget (March 1, 2016). The TextBlob measurements can therefore be cross-validated against the expected emotional responses to these events. The resulting positive mood time series are shown in Fig. 2 and are expressed in z-scores as given by in Eq. (1)

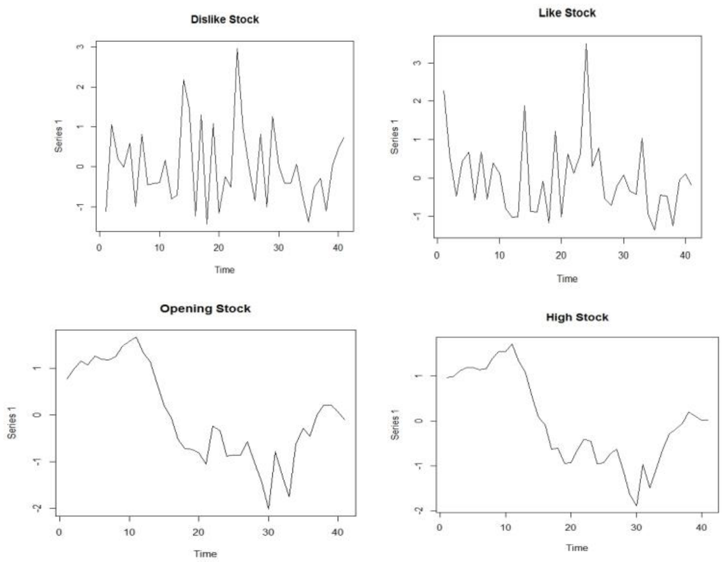

Fig. 2. Tracking public mood states from tweets posted between December 10, 2015 to March 10,2016 shows public responses to Annual Budget.

B. Bivariate Granger Causality Analysis

After establishing that our mood time series responds to significant socio-cultural events such as the Rail Budget and Annual Budget, we are concerned with the question whether other variations of the public's mood state correlate with changes in the stock market, in particular NIFTY Auto Index Opening/High/Low/Closing values. To answer this question, we apply the econometric technique of Granger causality analysis to the daily time series produced by TextBlob vs. the NIFTY Auto Index. Granger causality analysis rests on the assumption that if a variable X causes Y then changes in X will systematically occur before changes in Y. We will thus find that the lagged values of X will exhibit a statistically significant correlation with Y. Correlation however does not prove causation. We therefore use Granger causality analysis in a similar fashion to [8]; we are not testing actual causation but whether one time series has predictive information about the other or not.

Our NIFTY Auto Index time series, denoted Dt, is defined to reflect daily changes in stock market value, i.e. its values are the delta between day t and day t - 1: Dt = Auto(t)- Auto(t-1). To test whether our mood time series predicts changes in stock market values we compare the variance explained by two linear models. The first model (L1) uses only n lagged values of Dt, i.e. (D(t-1),…..,D(t-n)) for prediction, while the second model L2 uses the n lagged values of both Dt and the TextBlob mood time series denoted X(t-1),………,X(t-n).

We perform the Granger causality analysis according to model L1 and L2 for the period of time between December 10,2015 to March 10, 2016 to exclude the exceptional public mood response to the Rail Budget and Annual Budget from the comparison. TextBlob time series was produced for more than 100,000 tweets in that period, and the daily NIFTY Auto Index was retrieved from [25] for each day.

TABLE (I)

STATISTICAL SIGNIFICANCE (P-VALUES) OF BIVARIATE GRANGER-CAUSALITY CORRELATION BETWEEN MOODS AND NIFTY Auto Index IN PERIOD December 10, 2015 TO March 10, 2016.

	Lag	Like	Dislike
OPEN	1 day	0.73	0.6685
	2 day	0.5299	0.3725
	3 day	0.4136	0.343
	4 day	0.1775	0.2326
	5 day	0.3034	0.4084
	6 day	0.5875	0.5728
	7 day	0.6204	0.6909

	Lag	Like	Dislike
CLOSE	1 day	0.8024	0.6851
	2 day	0.7974	0.6937
	3 day	0.7786	0.4025
	4 day	0.939	0.4287
	5 day	0.6568	0.6415
	6 day	0.7195	0.7484
	7 day	0.8434	0.8627

	Lag	Like	Dislike
HIGH	1 day	0.7689	0.6989
	2 day	0.7795	0.5309
	3 day	0.3473	0.2791
	4 day	0.07219	0.205
	5 day	0.1903	0.4148
	6 day	0.4691	0.4946
	7 day	0.6419	0.6635

	Lag	Like	Dislike
LOW	1 day	0.7257	0.8009
	2 day	0.4717	0.5962
	3 day	0.5667	0.4297
	4 day	0.8306	0.3484
	5 day	0.5632	0.5169
	6 day	0.6309	0.6672
	7 day	0.5972	0.8009

Based on the results of our Granger causality (shown in Table I), we can reject the null hypothesis that the mood time series do not predict NIFTY Auto Index values with a high level of confidence. However, this result only applies to 1 TextBlob mood dimension. We observe that Positive sentiment has the highest Granger causality relation with NIFTY Auto Index for lags ranging from 4 to 6 days (p-values < 0.5). The other mood dimension of TextBlob does not have significant causal relations with changes in the stock market.

To visualize the correlation between X1 and the NIFTY Auto Index in more detail, we plot both time series in Fig. 3. To maintain the same scale, we convert the NIFTY Auto Index delta values Dt and mood index value Xt to z-scores as shown in Eq. (1) .

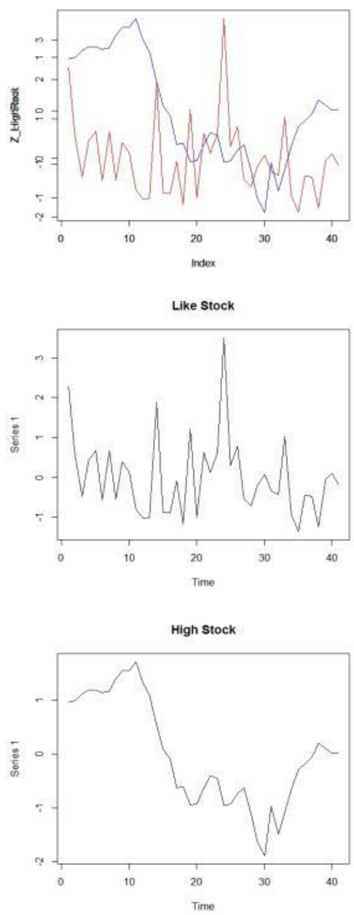

Fig. 3. A panel of three graphs. The top graph shows the overlap of the day-to-day difference of NIFTY Auto Index values (blue: ZDt) with the TextBlob Positive time series (red: ZXt) that has been lagged by 4 days. Where the two graphs overlap the Positive time series predict changes in the NIFY Auto Index High values that occur 4 days later. Areas of significant congruence can be seen.The middle and bottom graphs show the separate Like and NIFTY Auto Index time series.

As can be seen in Fig. 3 both time series frequently point in the opposite direction. Changes in past values of Positive (t - 4) predicts a similar rise or fall in NIFTY Auto Index values (t =0). The Positive mood dimension thus has predictive value with regards to the NIFTY Auto Index. The cases in which the t - 4 mood time series fails to track changes in the NIFTY Auto Index are nearly equally informative as where it doesn't. In particular we point to a significant deviation between the two graphs near Annual Budget where the NIFTY Auto Index goes down by more than 3 standard deviations from peak. The Positive curve however remains relatively flat at that time after which it starts to again track changes in the NIFTY Auto Index again. This discrepancy may be the result of the different views of users we selected as input. The deviation between Positive values and the NIFTY Auto Index on that day illustrates that unexpected news is not anticipated by the public mood yet remains a significant factor in modeling the stock market.

C. Non-linear models for emotion-based stock prediction

Positioning Our Granger causality analysis suggests a predictive relation between certain mood4 dimensions and NIFTY Auto Index. However, Granger causality analysis is based on linear regression whereas the relation between public mood and stock market values is almost certainly non-linear. To better address these non-linear effects and assess the contribution that public mood assessments can make in predictive models of NIFTY Auto Index values, we compare the performance of a Neural Network model [20] that predicts NIFTY Auto Index values on the basis of two sets of inputs: (1) the past 4 days of NIFTY Auto Index values, and (2) the same combined with various permutations of our mood time series (explained below). Statistically significant performance differences will allow us to either confirm or reject the null hypothesis that public mood measurement does not improve predictive models of NIFTY Auto Index values.

We use a NN as our prediction model since they have previously been used to decode nonlinear time series data which describe the characteristics of the stock market and predict its values. Our NN in particular is a three layer neural network .To predicts the NIFTY Auto Index value on day t, the input attributes of our NN include combinations of NIFTY Auto Index values and mood values of the past n days. We choose n = 4 since the results shown in Table II indicate that past n = 4 the Granger causal relation between Positive sentiment and NIFTY Auto Index decreases significantly. All historical load values are linearly scaled to [0,1]. This procedure causes every input variable be treated with similar importance since they are processed within a uniform range.

We had tried all combination of different values for prediction and map them as shown below.

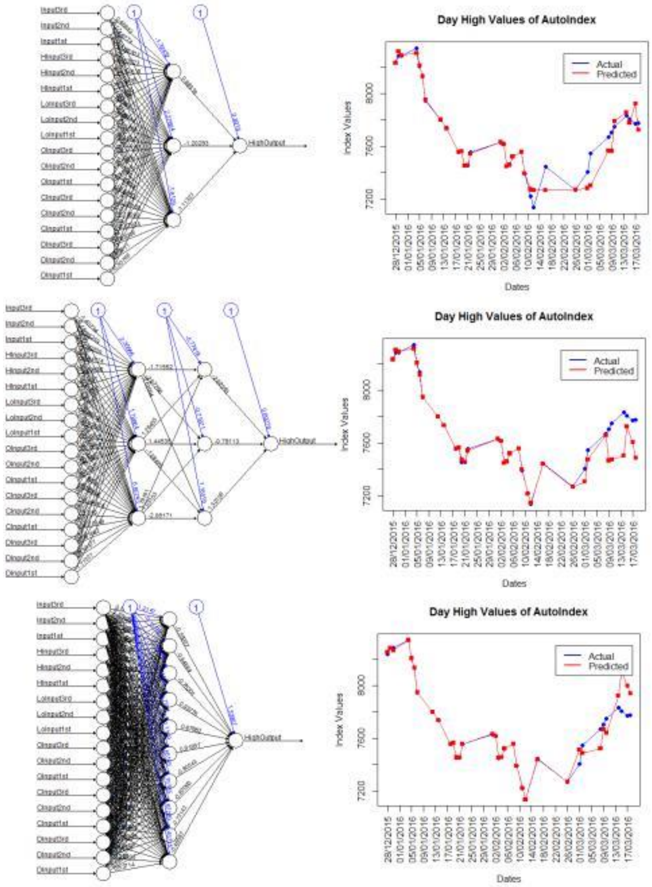

Fig (4) The left pane shows the different hidden layers combination used for prediction of NIFTY Auto Index. The right pane shows the overlapping of two graphs one is for actual values and second is for Predicted values. First and last NN are seems to be more predictive than second combination.

V. CONCLUSION

In this paper, we investigate whether public mood as measured from large-scale collection of tweets posted on Twitter is correlated or even predictive of Nifty Auto Index values. Our results show that changes in the public mood state can indeed be tracked from the content of large-scale Twitter feeds by means of rather simple text processing techniques and that such changes respond to a variety of socio-cultural drivers in a highly differentiated manner. The positivity of the public is thus predictive of the Nifty Auto Index. A Neural Network trained on the basis of past Nifty Auto Index values and our public mood analysis furthermore demonstrated the ability of the latter to significantly improve the accuracy of even the most basic models to predict Nifty Auto Index High values. Given the performance increase for a relatively basic model such as the NN we are hopeful to find equal or better improvements for more sophisticated market models that may in fact include other information derived from news sources, and a variety of relevant economic indicators. These results have implications for existing sentiment tracking tools as well as surveys of "self-reported subjective well-being" in which individuals evaluate the extent to which they experience positive and negative affect, happiness, or satisfaction with life [23]. Such surveys are relatively expensive and time consuming, and may nevertheless not allow the measurement of public mood along mood dimensions that are relevant to assess particular socio-economic indicators. Public mood analysis from Twitter feeds on the other hand offers an automatic, fast, free and large-scale addition to this toolkit that may in addition be optimized to measure a variety of dimensions of the public mood state.

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