Peoples Opinion on GST and Demonetization using Sentence Level Sentiment Analysis

Bharat R.Naiknaware[1], Seema Kawathekar[2], Sachin Deshmukh[3]
[1.2.3]*Department of CS and IT*
Dr. Babasaheb Ambedkar Marathwada University

***Abstract* -** We develop an automated system which extracts the sentiments from the online posts from twitter. Our system shows sentiment identification, which expresses opinion associated with each entity. Also it consists of scoring phase, which assigns scores to each entity, on which the tweets are classified. Finally we have leveraged Naive Bayes, Support vector machine and Maximum Entropy classifiers Algorithms to do the sentiment analysis on this myriad of data. We use Twitter, an online social networking and micro blogging tweets facility, which user can update related post in the form of content type is text, known as tweets, with 140-character limit. There are also many sources that express opinions of news entities (people, places, things) while publishing recent events. Sentiment Analysis, also called Opinion Mining, is one of the most recent research topics within the field of Information Processing. Textual information retrieval techniques are mainly focused on processing, searching or mining factual information. Textual information also has some objective as well as subjective characteristics. These elements are mainly opinions, sentiments, appraisals, attitudes, and emotions, which are the focus of Sentiment Analysis. Text sentiment analysis typically works at a particular level like phrase, sentence or document level. This paper we presents comparative study of various government announced schemes and we are predicted peoples opinion against that particular schemes by using sentiment analysis methods on different levels. Further it extends the literature on sentence level. Comparison of different machine learning techniques applied to the case of sentiment analysis in social media. Several machine learning methods were used during experimentation session: Naive Bayes, Maximum Entropy, and Support Vector Machines we tried to compare different techniques for preprocessing Social media data and find those ones which impact on the building accurate classifiers.

***Keywords* -** SVM, Naïve Bayes, Maximum Entropy MAE, ME, Sentiment Analysis

I. INTRODUCTION

Social media Sentiment analysis refers to the inference of people's views, positions and attitudes in their written or spoken texts. Before the coining of the term, the field was studied under names such as subjectivity, point of view and opinion mining. Nowadays, the field is rapidly evolving due to the rise of new platforms such as blogs, social media and user-generated reviews. A large body of work exists on the analysis of latent sentiment in social media platforms such as Twitter. The goal of these studies is to extract timely and relevant information as well as to judge widespread opinions and sentiment. Sentiment Analysis offers many opportunities to develop new applications, especially due to the huge growth of available information in sources such as blogs and social networks. For example, recommendations of items proposed by any recommender system can be computed taking into account aspects such as positive or negative opinions about those items. Review- and opinion-aggregation websites could collect information from different sources in order to summary or compose an opinion about a candidate, product, etc., thus replacing systems which require explicitly opinions or summaries. Therefore one of the most important fields where Sentiment Analysis has a greater impact is in the industrial field. Small and big companies, as well as other organizations such as governments, desire to know what people say about their schemes, products or members Sentiment analysis has been handled as a Natural Language Processing task at many levels of granularity. Depending on whether the target of study is a whole text or document, one or several linked sentences, or one or several entities or aspects of those entities, different NLP and Sentiment Analysis tasks can be performed. Hence, it is necessary to distinguish three levels of analysis that will clearly determine the different tasks of Sentiment Analysis;

A. Document level
B. Sentence level and
C. Entity/aspect/feature level [1].

A. Document Level Analysis - Document level considers that a document is an opinion on an entity or aspect of it. This level is associated with the task called document-level sentiment classification, the task is to classify whether a whole opinion document expresses a positive or negative sentiment For example, given a product review, and the system determines whether the review expresses an overall positive or negative opinion about the product. This task is commonly known as document-level sentiment classification. [2].

B. Sentence Level Analysis - The task at this level goes to the sentences and determines whether each sentence expressed a positive, negative, or neutral opinion. Neutral usually means no opinion. This level of analysis is closely related to subjectivity classification which distinguishes sentences (called objective sentences) that express factual information from sentences (called subjective sentences) that express subjective views and opinions. However, we should note that subjectivity is not equivalent to sentiment as many objective sentences can imply opinions.

C. Feature Level Analysis: Both the document level and the sentence level analyses do not discover what exactly people liked and did not like. Aspect level performs finer-grained analysis. Aspect level was earlier called feature level (feature-based opinion mining and summarization).Instead of looking at language **constructs** (documents, paragraphs, sentences, clauses or phrases), aspect level directly looks at the opinion itself. It is based on the idea that an opinion consists of a sentiment (positive or negative) and a target (of opinion). It is closely related to tasks like Feature-based Opinion Mining and Opinion Summarization.

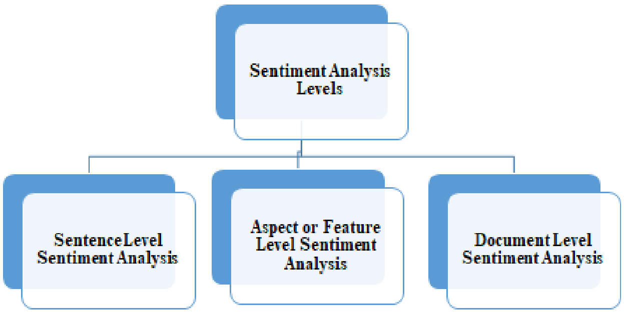

Fig1: Types of Sentiment Analysis Level

II. RELATED WORK

Vrushali K. Bongirwar [2] computing process of accuracy parameters in sentiment analysis Warih Maharani[3] highlighted difference between process mining and intention mining. In process mining some technique is used to process models by analyzing event logs where no apriori information is available and some α -algorithm may be used to model the behavior of the actor. In intention mining actor's intention is identified from event logs and produce intentional process models. Novel approaches on modeling and inferring users actions in a computer is proposed [3] using two linguistic features-keyword and concept features. Luiz F. S. et.al [4] considered the problem of classifying tweets documents not by topic, but by overall sentiment. They employed Naïve Bayes, maximum entropy classification, and support vector machines, which do not perform well on sentiment classification. Rohit Joshi et al [3] present Sentiment Analyzer (SA), which detects all references for the given subject, and determines sentiment in each of the references using natural language processing (NLP) techniques. R. Nivedha, N. Sairam [5] A Machine Learning based Classification for Social Media Messages. Lopamudra Dey [6] et al Sentiment Analysis of Review Datasets Using Naïve Bayes'and K-NN Classifier here Naïve Bayes machine learning techniques compare with K-nn, Bhumika M. Jadav[10] et al Sentiment Analysis using Support Vector Machine based on Feature Selection and Semantic Analysis here authors aim of paper is to find best effective features which provide better result and also provide better feature selection method. They have also express that how unigram feature set can be reduced to get better result.

III. EXPERIMENTAL SETUP

The data preparation step performs necessary data preprocessing and cleaning on the dataset for the subsequent analysis. Some commonly used preprocessing steps include removing non-textual contents and markup tags (for HTML pages), and removing information about the reviews that are not required for sentiment analysis, such as review dates and reviewers' names. The review analysis step analyzes the linguistic features of reviews so that interesting information, including opinions and/or product features, can be identified. Two commonly adopted tasks for review analysis are POS tagging [1] and negation tagging. After this phase, sentiment classification is performed to get the results.

Datasets Collection from Twitter -We are collecting twitter datasets is used to collect a corpus of text posts and a dataset is formed of three classes: positive, negative and neutral sentiments. We are using Indian government announced schemes in 2017 like Budget2017, Demonetization, Digital India, GST Kashmir, Make in India, Swach Bharat, the data on twitter was all datasets collected in March 2017 and after completion of one year we are collected GST and Demonetization tweets for the purpose of comparative study of people's opinion.

IV. FEATURE EXTRACTION

The collected dataset is used to extract features that will be used to train the sentiment classifier. Experimentation is carried out using n-gram binary features. The process of obtaining n-grams from the Twitter post is as follows.

A. Filtering: here we are Removing URL links that are in datasets files before preprocessing

B. Tokenization: Tokenization is the process of breaking a stream of text up into words, phrases, symbols, or other meaningful elements called tokens. The list of tokens becomes input for further processing such as parsing or text mining. Tokenization is useful both in linguistics we segment text by splitting it by spaces and punctuation marks. However, we make sure that short forms such as "din't", "w'll", remain as one word.

C. Removing stop words: we remove articles ("a", "an", "the") from datasets.

D. Removing numbers, punctuation, and unnecessary spaces: e.g. Photoset httptco46iM8j8pkt after preprocessing is obtained as Photoset https://t.co/f9zDs2Zr9v Missing values: NA is assigned to the missing values.

E. Converting to lower case: All the letters in the sentences are converted into lower case.

F. Constructing n-grams: we make a set of n-grams out of consecutive words. A negation (such as "no" and "not") is attached to a word which precedes it or follows it. For example, a sentence "I do not like fish" will form two bigrams: "I do+not", "do+not like","not+like fish"

V. GENERATE SCORE FOR SENTIMENT ANALYSIS

The most important part of sentiment analysis to generate score each tweet, score. Sentiment ( ) function is used to iterate through the input text. It strips punctuation and control characters from each line using in R Programming platform regular expression-powered substitution function, and matches against each word list to find matches.

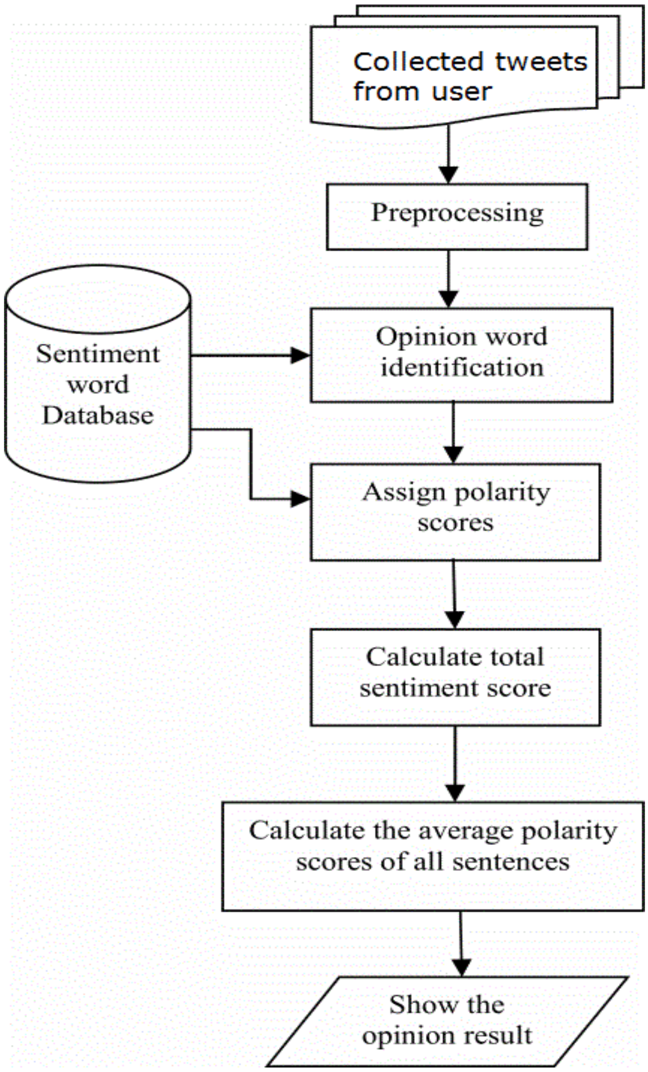

Fig 2: Methodology

The score Sentiment ( ) function assigns score to the tweets using the formula as Score = sum (pos.matches) – sum(neg.matches) The score is maintained between -4 to 4. 4 and 3 represent very positive -4 and -3 represent very negative 2 and 1 represent positive -2 and -1 represent negative if the score turns out to be zero, it is classified as neutral.

VI. MACHINE LEARNING METHODS

We experimented the three standard Machine Learning algorithms: Naive Bayes, Support vector machine and Maximum Entropy. To implement these machine learning algorithms, there is need to have a mechanism which categorizes words (or combination of words) of the post by its sentiment. Hu and Liu's "opinion lexicon" categorizes nearly 6,800 words as positive or negative and can be downloaded from Bing Liu's web site:http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar. The lexicon has been divided into two text files, one containing a list of positive words and the other containing negative words. Each file begins with some documentation, which we need to skip and is denoted by initial semi-colon (";") characters.

Result Analysis - We are using the classifiers that are compared based on the accuracy measures such as Mean error (ME), Root mean square error (RMSE), Mean absolute error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE). This are accuracy measurement parameters in sentiment analysis. Here we are comparing majorly two important parameters i.e. ME (Mean error) and (MAE) Mean absolute error the simplest measure of forecast accuracy is called Mean Absolute Error (MAE). MAE is a quantity used to measure how close forecasts or predictions are to the eventual outcomes or in other words we can say it simply the mean of the absolute errors. The absolute error is the absolute value of the difference between the forecasted value and the actual value.

MAE tells us how big of an error we can expect from the forecast on average. Cort J. Willmott et.al [19] indicates that MAE is the most natural measure of average error magnitude also the Mean Error is important here we are finding the error value of particular datasets than RMSE. Evaluations and inter-comparisons of average model performance error should be based on ME and MAE. Table1 shows the ME and table 2 shows MAE for the datasets Budget2017, Demonetization, GST2017, Digital India, Kashmir, Make in India, Startup India and Table 3 shows the intensity of Datasets.

Table 1: ME (Mean Error) of Datasets

Classifier	ME						
Datasets	Budget 2017	Demonetization	GST2017	Digital India	Kashmir	Make in India	Startup India
Naïve Bayes	45	97	15	20	27	35	30
SVM	66	78	31	47	91	12	36
Maximum Entropy	60	35	39	39	12	10	28

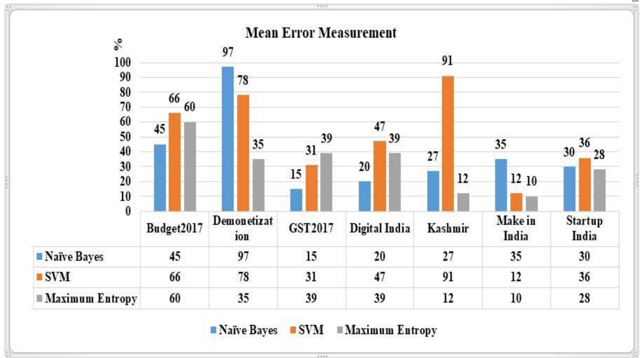

Table 2: MAE (Mean Absolute Error) of Datasets

Classifier	MAE						
Datasets	Budget 2017	Demonetization	GST 2017	Digital India	Kashmir	Make in India	Startup India
Naïve Bayes	33	15	59	38	27	68	49
SVM	66	78	31	47	91	12	69
Maximum Entropy	60	35	39	29	12	10	28

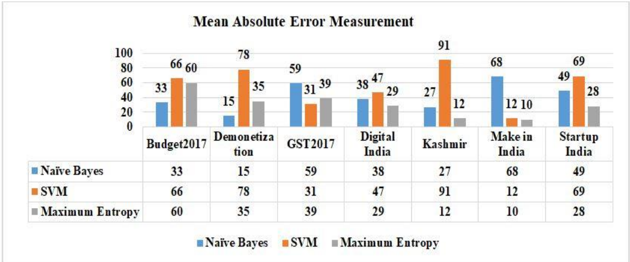

Table 3: Intensity of Tweets polarity in Datasets

Trend Name	Positive Sentiments	Negative Sentiments	Neutral Sentiments	Tweets used
#GST4India	2040	416	2544	5000
#Startupindia	1831	305	2864	5000
#SwachBharat	93	10	22	125
#FinBudget	1830	304	2866	5000
#Digital India	2070	620	2310	5000
#Demonetization	1866	2769	4347	8980
#MakeInIndia	2638	482	1880	5000
#Kashmir	1034	1579	2387	5000

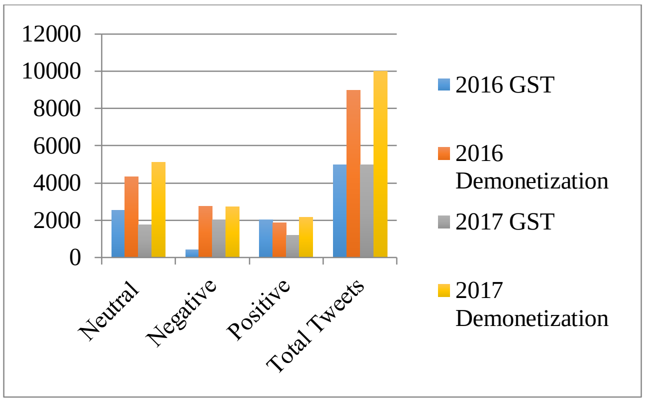

Table 4: Comparative study between year 2016 and 2017 specifically GST and Demonetization

Year	Scheme	Neutral	Negative	Positive	Total Tweets
2016	GST	2544	416	2040	5000
	Demonetization	4347	2769	1866	8982
2017	GST	1748	2033	1219	5000
	Demonetization	5108	2714	2178	10000

VII. CONCLUSIONS AND FUTURE SCOPE

We studied people's opinion regarding GST and Demonetization after completed one year in both schemes peoples are having negative opinion we shown in table 4 details about result. also mentioned Government schemes in this paper peoples are given their opinion through twitter peoples are positive with MakeInIndia and others schemes are Neutral opinion. As technical performance with machine learning classifiers we found the results like if the MAE is smaller than accuracy is more. The results show that the performance of the classifiers is same. There is marginal difference in the MAE. The performance of the classifiers was made for seven datasets (Budget2017, Demonetization, GST2017, Digital India, Kashmir, Make in India, Startup India). In the Budget2017 dataset Naïve Bayes performs best, In Demonetization dataset Naïve Bayes performs best. In the GST2017 SVM is showing best performance, whereas in the Digital India, Kashmir, Make in India and Startup shows Max Entropy performs best. Here we are also find the Mean Error for predicting the Mean Absolute Error easily.

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