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Enhancement Schism Opinions in Twitter with Social Media Analysis (ESOTA)

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***Abstract* - Social media most enhancement to a Twitter part-of-speech classification, building make use of more than a few new twitonomy and twitter capable of documents of sentence. In the midst of these changes, the classification speed enlarged from speed is 70 times faster. In addition, It long-drawn-out our Twitter indication to prop up a broader variety of sentence typeset, emoticons, and Uniform resource Locators. Finishing comment on and high up on a new twitter dataset TFISFT, Opinosis that is more statistically delegate of English-language Twitter (ELT) as a in one piece. In this paper, Twitter knowledge of collecting more tweets, affecting sentiment analysis to evaluate positive, neutral or negative sentiments, and preliminarily plotting the collision on propagation. Sentiment analysis is currently used to investigate the ramifications of experiences in social media, search opinions about tweets and understand various aspects of the communication in Web-based communities. The new classification is on the demolish into page as (#NNOOS@) along with the new comment and data and large-scale sentence of word summarizing texts for certain purposes Support Vector Machines (SVM) are very good algorithms used for classification and have been also used in information extraction. Learning in SVM is treated as a classification problem and set of classification set of training set using solving (#NNOOS) each is represented as a vector in a space of features and SVM tries to find an apprehensive even which separates positive from negative instances inputs and the outputs Polarity classification on social media analysis.**

***Index Terms* - Social media, Tweetdataset, SVM Algorithm, English-language Twitter, ELT.**

I. INTRODUCTION

Social Media Monitoring (SMM) means the identification, observation, and analysis of user-generated social media content for the purpose of market research. It work is a social structure of people, related (directly or indirectly) to each other through a common relation or interest. Social Sentence of words analysis (SNA) is the study of social Sentence of words s to understand their structure and behavior. Two main types of textual information. 1. Facts and Opinions means factual statements be capable of imply opinions. Most current text information processing methods (e.g., Web search, text mining) work with factual information.2.Sentiment analysis or opinion mining means computational study of opinions, sentiments and emotions expressed in text.

Natural Language Processing (NLP)

Specifically, it is the process of a computer extracting meaningful information from natural language input & any | producing natural language output. Usually more challenging questions Vector space models Linguistics means morphology, syntax, semantics, lexicon in base mode (#NNOOS@).Training sets uses SVM, Vector space, Terms uses literal strings, stemming, twitter of related terms. Rules – simple – position in text (Title, body, url).

Opinion

According an opinion consist of the following 4 parts: topic, opinion holder, claim and sentiment. That is for each opinion there is holder who believes a claim about a topic and then associates a positive, negative or neutral sentiment with the claim.

1.3.1 TWITTER

Twitter is a overhaul that lend a hands group build and contribute to proposals and in sequence instantaneously. It recommends an straightforward technique to follow trends, stories and shattering intelligence composing beginning lines approximately the humankind and it furthermore make available apparatus to hang about in lay a hand on with other populace, commerce's in addition to social origins. Accurately, Twitter is an in sequence media prepared up of 140-character messages called tweets [29]. Tweets possibly will hold associations to other websites, piece of writings, snapshots and videotapes.

1.3.2 TWITTER IN SEGMENTATION CLASSIFICATION

In the perspective of Twitter, a "Sentence" is some expression or axiom in need of attentional preceded by a hodgepodge sign (#) [3]. sentence are make use of to recognize positions on a unambiguous focus for occurrence, when a user be on the same wavelengths on a sentence see other tweets holding the similar theme. Sentence be capable of come about wherever in a tweet at the beginning, middle, or end. that become very popular are often considered trending topics [30].A tweet that a user forwards to all of her "followers", selected make contact withs Twitter is acknowledged as a "Replay tweets", (Ts). tweets are frequently used to get ahead of along news or other important discoveries on Twitter. It be supposed to be scrutinized that tweets always retain innovative acknowledgment.Sentiment analysis or opinion mining is apprehensive with the make use of of natural language processing and computational linguistics to identify and extract subjective information in text materials, such as tweets. A wide range of human moods can be discovered through sentiment analysis, but a major focus has been identifying the polarity of a given text [13]—i.e., to automatically recognize if a text is positive, negative or neutral.

II. RELATED WORK

Mahmoud Elgamal et al [1], It utilize tweets during Hajj to do sentiment analysis; the tweets are preprocessed by experience three phases; tokenization, normalization, and part of speech (POS) tagging. In the final step, Naïve Bayes classifier used toclassify tweet as positive or negative by comparing each word in the query tweet with the labeled words in the lexicon. Buettner, R. (2016) [1A] et al career-oriented social Sentance of wordsing sites I investigated their job search behavior. For further IS-theorizing I integrated the number of a user's contacts as an own construct.

S. Zanella and I. Pais et al [3] However, professional "recruiters seem do distrust the number of contacts of an applibe capable oft as a sort of 'noisy' information"[4] This equates to 22 percent of all time online or one in every four and half minutes. For the first time ever, social Sentance of words or blog sites are visited by three quarters of global consumers who go online, after the numbers of people visiting these sites increased by 24% over last year.

Cole-Lewis, H.; Varghese, A.; Sanders, A.; Schwarz, M.; Pugatch, J.; Augustson et al [9] establish a supervised machine learning algorithm to build predictive classification models that assess Twitter data for a range of factors related to e-cigarettes.[10].experience of collecting more than 175,000 tweets, applying sentiment analysis to measure positive, neutral or negative feelings, and preliminarily mapping the impact on dissemination. Sentiment analysis is currently used to investigate the repercussions of events insocial Sentance of words s, scrutinize opinions about products and services, and understand various aspects of the communication in web-based communities.Wonchul Seo, Janghyeok Yoon, Hyunseok Park, Byoung-youl Coh, Jae-Min Lee, Oh-Jin Kwon et al [11] the presented systematic approach be capable of be a basis for an R&D planning system that be capable of help R&D planners in performing product-oriented technology planning activities.

Malk Eun Pak, Yu Ri Kim, Ha Neui Kim, Sung Min Ahn, Hwa Kyoung Shin, Jin Ung Baek, Byung Tae Choi et al [12] generic framework which It used to characterize the relationships between 10 genes reported associated with asthma by a previous GWAS. The results of this experiment showed that the similarities between these 10 genes were signifibe capable oftly stronger than would be expected by chance (one-sided p-value < 0.01).Matic Perovšek, Janez Kranjc, Tomaž Erjavec, Bojan Cestnik, Nada Lavračet et al [13] comparison of document classifiers and of different part-of-speech taggers on a text categorization problem, and outlier detection in document corpora.

Sultan M. Al-Daihani, Alan Abrahams A Text Mining Analysis of Academic Libraries' et al[14] importance of using data- and text-mining approaches in understanding the aggregate social data of academic libraries to aid in decision-making and strategic planning for patron outreach and marketing of services.Imran Ali, Yufan Guo, Ilona Silins, Johan Högberg, Ulla Stenius, Anna Korhonen et al [15] integrated in real-life risk assessment, could help and signifibe capable oftly improve the efficiency of the process.

Christopher Meaney, Rahim Moineddin, Teja Voruganti, Mary Ann O'Brien, Paul Krueger, Frank Sullivan et al [16] used a text-mining approach to determine if a specific statistical/epidemiological method was encountered in a given article. It report the proportion of articles using a specific method for the entire cross-sectional sample and also stratified into three blocks of time (1995–2005; 2006–2010; 2011–2015).

Jitendra Jonnagaddala, Siaw-Teng Liaw, Pradeep Ray, Manish Kumar, Nai-wen Chang, Hong-Jie Dai et al [17] the text mining system was reliable, but there was a signifibe capable oft amount of missing data to calculate the Framingham risk score.Constantine Boussalis, Travis G. Coan et al [18] introduce a methodology to measure key themes in the corpus which scales to the substantial increase in content generated by conservative think tanks over the past decade.

Thien Hai Nguyen, Kiyoaki Shirai, Julien Velcin et al [19] the accuracy average over 18 stocks in one year transaction, our method achieved 2.07% better performance than the model using historical prices only. Furthermore, when comparing the methods only for the stocks that are difficult to predict, our method achieved 9.83% better accuracy than historical price method, and 3.03% better than human sentiment method Aliaksei Severyn, Alessandro Moschitti, Olga Uryupina, Barbara Plank, Katja Filippova[20].

III. 3.0 PROBLEM

The new user and do not have that many followers, the use of Twitter as a research tool can be limited. Linking it with other social Media such as Facebook (via the Twitter application) and LinkedIn, where you might have more friends, will help you build up a Twitter presence.Also, sometimes 140 characters are just not enough to get the message across;English charater for discussion of complicated issues may need to contact users directly tweets, they are willing. Sentiment analysis can be viewed as an application of text categorization, which dates back to the work on probabilistic text classification . The main task of text classification is label texts with a predefined set of categories. Text categorization has been applied in other areas such as twitter indexing, tweets filtering, word sense disambiguation.One of the central issues in text classification is how to represent the content of a text in Positive & negative ,nenutral order to facilitate an effective classification. From researches in information repossession systems, one of the most popular and successful method is to represent a text by the collection of terms appear in it. The similarity between documents is defined by using the term frequency inverse sentence frequency (tfisf). In this approach, the terms or features used to represent a text is determined by taking the union of all terms that appear in the collection of texts used to derive the classifier. This usually results in a large number of features. Therefore, dimensionality reduction is a related issue that needs to be twitter messages.

3.0.1 LIMITATION

In accomplishing this learning by means of the new techniques of Twitter in sequence mining, sentiment Analysis and ploting of tweets, stumble uponed a add up to of significant limitations. First were limited in the add up to tweets that could be bring togethered with each indicateing that a number of very well-knownly used sentence e.g., #onde, #yellow holded truncated data. This could foregone conclusion our results. However collected over 5,00,000 tweets and as such have a relatively robust sample. Second,we used a limited set of hodgepodge-tags based on expert opinion.

3.1 BACKGROUND

seminal strong point of connection of Twitter language with Positive Sentiment (measure of Prior schism): prearranged a sentence/expression recommend a achieve between 0 (buck) and 1 (uppermost) with the purpose of is problem-solving of the strong point of connection of with the purpose of sentence/expression with positive sentiment. If a sentence/expression is more positive than another one, it should be allocateed a qualifiedly top keep count.

DataSet:

In this section, we describe the process of collectingand annotating our datasets of short social media text messages. We focus our discussion on the 2015 datasets; more detail about the 2013 and the 2014 datasets can be found in (Nakov et al., 2013) and (Rosenthal et al., 2014).

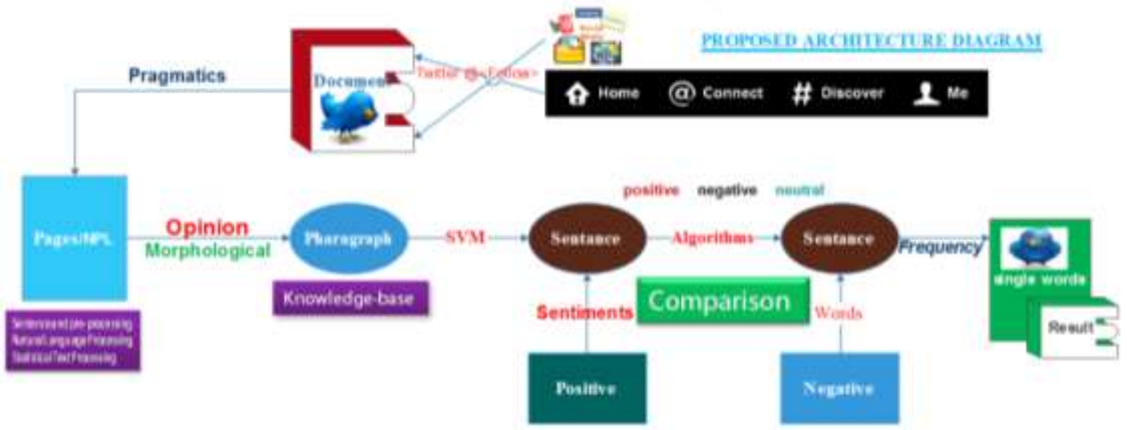
3.1.1 PROPOSED WORK

the task is to produce shorter, summary version of an original document of sentance investigation methods used above mainly include sentence of word speed, based priority score, with sentiment as display for classification, and lexicon based approaches classifiers. In our proposed approach It are going to implement multi-class classifier for analyzing sentiments of public on political domain with taking into consideration sentance negative as well as positive approaches. In this do research evaluated a outsized data set from which tried to establish the reputation of a prearranged Message in more than a few points. In classify to do this evaluated tweets from Twitter. Tweets are a dependable resource of in sequence most importantly because public tweet .

EXPERIMENTAL SECTION:

To transmit out effort began by selecting Twitter [28] as the display place where follow a line of investigation was embark on . Twitter is a high-quality establishing point for social media investigation for the reason that its abusers tend to contribute to their opinions unlockly with the broad-spectrum public, as contrasting to Facebook where communications are frequently hush-hush or partially-hush-hush classified to nominated acquaintances or “acquaintances”.

3.1 PROPOSED ARCHITECTURE DIAGRAM



The goal of machine learning is to design algorithms that improve their performance on a particular task using examples. The computer program “successful” examples of the task it is supposed to carry out and automatically learns to perform the task with some degree of success. Performance is measured on previously “beautiful” examples[9]. The opposite of using machine learning to solve a task is to do it by hand. That is, by writing out explicit rules using your own understanding of the task. As a first step in developing your understanding and appreciation for machine learning[10] in this program a computer to solve a complex problem by hand. The task is to classify retweets into positive or negative sentiment. A analysis has a positive sentiment if the author liked the movie and a negative sentiment . This is a task that humans be capable of perform fairly well. In this homework, you will try to get a computer to do it! This exercise is similar to the one presented in Pang et al. [11], which describes one of the first attempts at using machine learning for sentiment analysis.

IV. 4.0 IMPLEMATION:

Bag of Words approach was used for sentiment analysis.Stemming is a each tweet was stemmed into the group of English words.Matching is a match of each sentence in word was searched in the lexicon database (Sentence total 6135 words in the lexicon; 2230 positive and 3905 negative)Scoring is Positive and negative matches were summed to define a score of each tweet .Polarity is calculate (P-N)/(P+N), where P=total sum of positive sentence sentiment words; N=total sum of negative sentence sentiment words Results were grouped and combined on a monthly basis.

4.1 WORD PROCEDURE

Relations among word surface forms and their senses follow Homonomy means same form, but different meaning Mulitonominy : same form, related meaning[12].Synonymy means different form, same meaning (e.g. singer, vocalist) Textonominy is one word denotes a subclass of an another.Word frequencies in texts have power distribution[13].

4.2 SOCIAL MEADIA

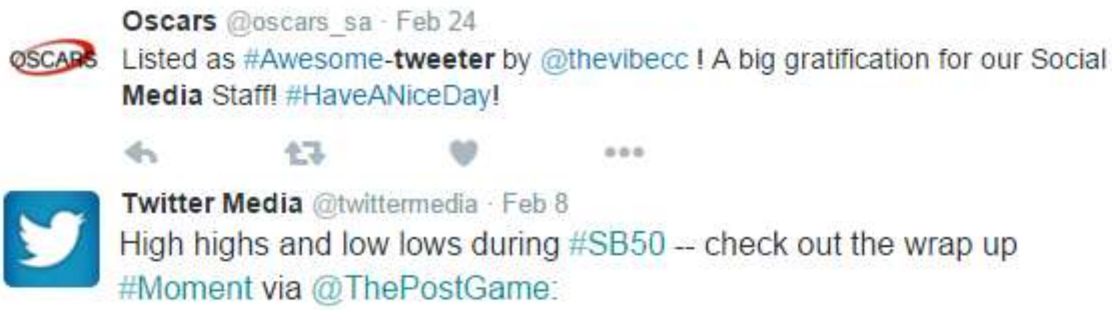
Social meadia twiter small number of very frequent words in big number of low frequency words.Stop-words are words that from non-linguistic view do not carry information.

4.2.1 Orginal Text 140 Charater:

TRUMP MAKES BID FOR CONTROL OF RESORTS Casino owner and real estate Donald Trump has offered to acquire all Class B common shares of Resorts International Inc, a spokesman for Trump said. The estate of late Resorts chairman James M. Crosby owns 340,783 of the 752,297 Class B shares. Resorts also has about 6,432,000 Class A common shares outstanding. Each Class B share has 100 times the voting power of a Class A share, giving the Class B stock about 93 pct of Resorts' voting power.

4.2.2 Twitter Analysis Data's

[Tid@RESORTS624][TwitterText#CLASS487][TwitterDate#TRUMP:0.367]
[TwiterPositve@VOTING:0.171@dataset][TwitterNegative#ESTATE:0.166]
[TwiterNeutral@POITR:0.134][T#CROSBY:0.134][TidU#CASINO:0.119]
#DEVELOPER:0.118][@SHARES:0.117][@OWNER:0.102][#SHAR:0.23]
[#DONALD:0.097][#COMMON:0.093][@GIVING:0.081][@OWNS:0.080] [@MAKES:0.078][#Jm@]
[@TIMES:0.075][@SHARE:0.072][#JAME:0.070]



4.3 SVM ALGORITHMS

Input: *set of documents SD in the form of TFISFT numeric vectors*
each document has label +1 (# positive class) or -1 (@negative class) or(neutral)0
Output: *non linear model w_i (one weight per word from the vocabulary)*
Algorithm: *Initialize∑ the model w_i by setting word Ω weights to 0*
Iterate ∂ through documents in sentence chararter N times
For Text s from SD in sentence using text // Using current model w_i classify sentance d
*if sum(sd_i *$w_{i*\sum*\partial}$) >= 0 then classify sentance as positive α else classify text in sentance as negative*
if document classification is wrong then $\sum sd_i*\omega*\partial$
// adjust weights of all words occurring in the document
*$Sw_{t+1} = w_t$ +sign(true-class) * Beta (input limitation Beta>0)*$\omega(sd_i)$*
// where sign(positive) = 1 and sign(negative) =-1

4.6 FREQUENCY SPECTROGRAM: Basic sounds in the signal (40-50 phonemes)(e.g. "a" in "cat").Template matching against db of phonemes.Using dynamic time warping (speech speed). It constructing words from phonemes (e.g. "th"+"i"+"ng"=thing).Unreliable/probabilistic phonemes (e.g. "th" 50%, "f" 30%).Non-unique pronunciations (e.g. tomato),statistics of transitions phonemes/words (hidden Markov models.

$$Phara(Doc \mid Sen) = \frac{Phara(Sen) \prod_{Word \in sen} Phara(Word \mid seq)^{Freq(Sen,Word)}}{\sum_i Phara(Sen_a) \prod_{Word_i \in sen} Phara(Word \mid seq_a)^{Freq(Word_G,Sen)}}$$

Document is represented as a set of Pharagraph(Phara) sequences(seq) Sentence(sen).Each classifier has two distributions: Phara(Word|seq), Phara(Word|seqa).calculated Phara(pos|Doc) is high meaning that the classifier has Phara(W|postive)>0 for at least some W from the document (otherwise, the prior probability is returned, Phara(negative) is about 0.90).

$$\text{Sentance}(q,d) = \frac{V(q) \times V(d)}{|V(d)|} = \frac{\sum_{t=1}^{n} w_{q,t} \times w_{d,t}}{\sqrt{\sum_{t=1}^{n} w_{d,t}^2}}$$

V(d) – term frequency (number of word occurrences in a sentance).W – Sentance frequency (number of documents containing the word).N – number of all documents of sentence in words.T – relative importance of the word in the Sentence.V-Text Anlaysis Sequence .

Y = T x S x C x I where,Y: denotes the result of the 4 elements,T: Trend;S: Seasonal Component;C: Cyclical Component, I: Irregular Component.

(o_j, f_{jk}, so_{ijkl}, h_i, t_l),where o_j- is a target object.f_{jk}- is a feature of the object o_j.so_{ijkl} is the sentiment value of the opinion of the opinion holder h_i on feature f_{jk} of object o_j at time t_l. so_{ijkl} is +ve, -ve, or neu, or a more granular rating. h_i is an opinion holder. t_l is the time when the opinion is expressed.

4.7 SYNTACTIC ANALYSIS: Rules of syntax (grammar) specify the possible organization of words in sentences and allows us to determine sentence's structure(s).Parsing is given a sentence and a grammar checks that the sentence is correct according with the grammar and if so returns a parse tree representing the structure of the sentence.

V. 5.0 DISCUSSION:

It observe that the speed saturates after types of separation is the idea that everyone is on average approximately steps away, by way of introduction, from any other person in the world.For Twitter this distance is found to be 4.67 .Web pages sizes ,Web page connectivity,Web connected components' size,we b page access statistics,

1. It has been long-established by this analysis that, it is feasible to bring together, pre-development, Discover and think about twitter social data using java API statistical software unfasten starting place implement correspondence.

2. It is feasible to be appropriate text mining assignments and sentiment analysis for twitter data to analyse abuser throw in analysiss for armed forces.

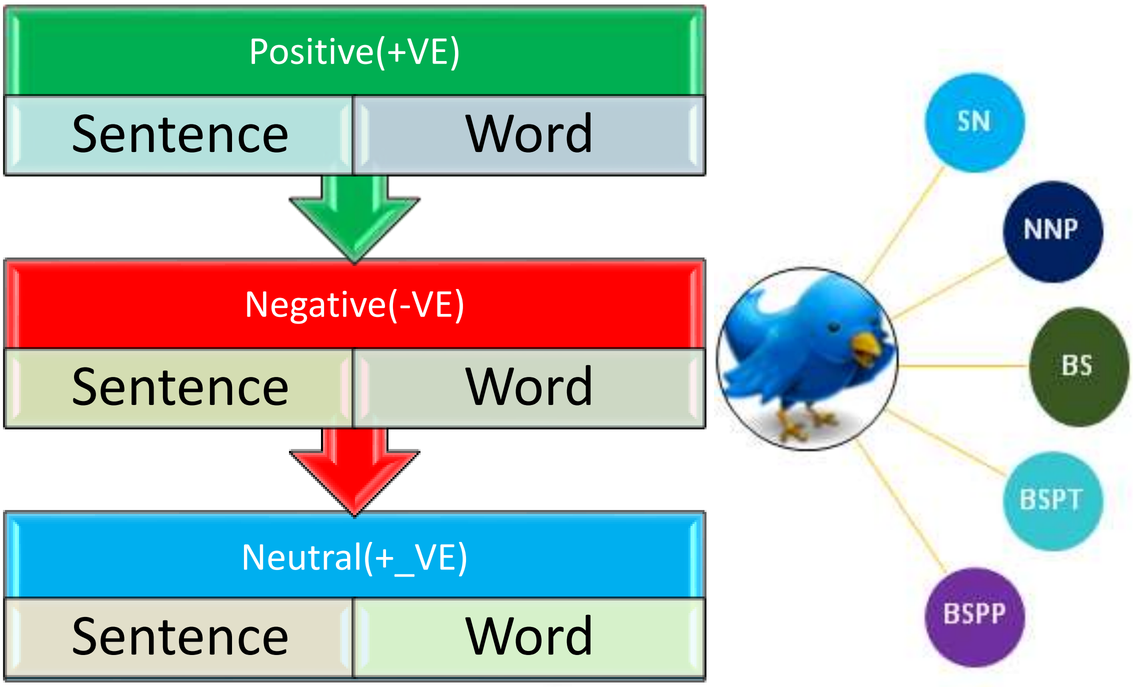
3. It will make available a ready for action advantage social media service providers to analyse their abuser observations considering their twitter service by means of social media data.This will be of assistance them get better their service significance and enhanced cope their friends relationship.

4. The portray come within reach of pertinent on other social media data sources such as Twitter.

This comprehensive that tune-up make the most of their user opinions engenderd from social media following and investigation by become accustomeding their advertising arrangements, service cleverness relevantly. An significant point of view for expectations effort could be fabricatting social media following and scrutinizzing classification as opinions are varying in the fullness of time. furthermore it is also important to employ un-supervised techniques in sentiment analysis and opinion mining for improving the Service spirited significance and the tweets connection supervision. In accumulation to measure up to various sentiment classification performances utilised for opinion mining. This more social media can be second-hand as a implement for tweets using opinion mining. The deposit out to ascertain if a social media conduit approximating Twitter could make available useful facts about the unrestricted perspective along with the social propagation of the concept nature language Processing. In responsibility so we have illustrated techniques of data get togethering, functional an up-and-coming line of attack, sentiment analysis and ploted the hodgepodge tag , tweets and Social media connected to comfortable about nature and language. Sentiment analysis has until that time been used to way opinion about Twitter reforms over time [12]. Another study examined the use of Twitter in the propagation of ideas about antibiotic use, using traditional methods to manually code the information in tweets [11]. This engaged supplementary engine-based come within reach of challenged to discover concerns and tests connected with these schemes and the longing to make the most of on the "big data" available.

5.0.1 NEW MODEL TWITONOMY ANALYSIS :

In view of the fact that add up to twitonomys available on a daily basis is too high (on a typical day, more than 500 million twitonomy are available an average of 5700 twitonomy per second .In this recoverd the twitonomy for learning by means of the unfasten starting place, Twitter application programming interface (API) annals twitonomy. At the time we performed learning only able to repossess tweets less than 7 days old, and we could only place 180 requests for tweets every 15 min. To collect such tweets, concernd a separate request for each hashtag via the Twitonomy rummage around API in other words, performed a separate repossession process(Speed) for each hodgepodgetag in Learning.The Twitter Search API performs similarly to the rummage around feature available in twitonomy. However,the Twitter Search API focuses on relevance, as opposed to completeness, which represents that some chirrups and users may be missing from the rummage around results. In any case, at the time or study, the Search API represented the most convenient way to retrieve tweets for purposes.To accumulate as many tweets as possible ideally all the tweets published for each of the hodgepodgetags preferred concernd reservation twice a day. Certain tweets communicating to particular hodgepodge tags were captured in the morning and once again in the evening when the number of tweets published for those hodgepodge tags on a particular day was diminutiver than the number of tweets that allowed to take back. For the same reason, some of the tweets incarcerated in the evening were summon up the following morning too.



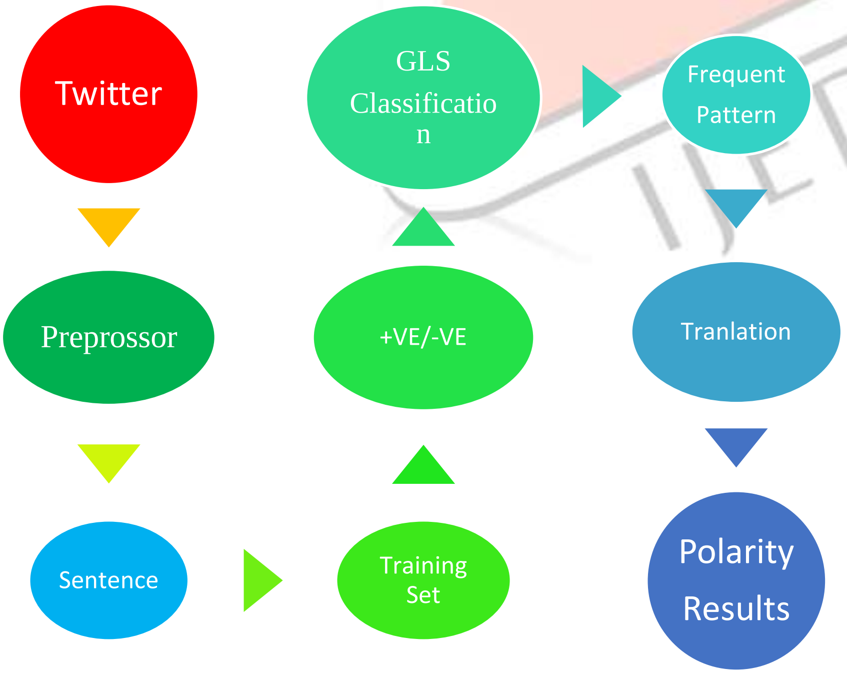
SN (singular noun), NPN (Natural plural noun), BS (verbs), BSPT (verb, past tense), BSPP (verb, past participle),PP(preposition), AJ (adjective), CJ (conjunction, e.g., "and", "or"), PN (pronoun), and MA (modal auxiliary, e.g., "be capable of", "will").

5.1 NEW NATURAL OPIOIN OF SENTENCE(NNOOS)

(1) The sentiment polarity, which can be positive =>"The Rose is Beautiful" negative=>"the Rose is Cost-low" neutral=>"The Rose is Pink".

(2) The sentiment strength, which is a real number value between 1 and 1 that expresses how negative or positive the sentiment is zero means that the sentiment is neutral, negative values refer to negative sentiment and positive values refer to positive sentiment.

(3) A Boolean value to point toward whether the sentiment is mixed i.e., both positive and negative.Memorandum with the purpose of the similar tweet or twitonomy announcement in wide-ranging can be negative about a Sentence and positive about something else.



For illustration purposes, Table 2 displays a random sample of tweets taken from our study together with their corresponding polarity, score and mixed values, as retrieved from AlchemyAPI. For research purposes, AlchemyAPI offers its services for free. However, it only allows 1000 transactions daily—determining the polarity of one tweet represents a single transaction. From the 1000 transactions that we were allowed daily, we kept 5 for testing, and then we submitted a daily batch of requests for the polarity of 995 different tweets. Although the testing was only indispensable for the first few days, when our experience in using AlchemyAPI was limited, we maintained the same approach for the rest of the experiment, as this preserved a constant number of transactions daily without exceeding the daily limit.

Rα (T) = cost - complexity measure of the tree T
= R(T) + α * | T |
= misclassification cost + α * (# of terminal nodes in T)
= misclassification cost + α * (complexity of T)
α = polarity placed on complexity

It took 178 consecutive days—i.e., nearly 6 months—to determine the polarity of the entire
collection of tweets in our experiment (176,494). We could have completed the processing earlier, by exclusively requesting the polarity of original tweets and assigning the same polarity to all the retweets—this would have saved us 80 days of processing, approximately. However, retweets frequently remove the last few characters of an original tweet, because there is not enough space to keep the whole content posted initially—recall that tweets cannot be longer than 140 characters (occasionally, retweets also contain additional content—for example, a small comment that constitutes what is known as a quote tweet). Since the polarity scores supplied by AlchemyAPI are based on the whole content, and this may change slightly between a tweet and a retweet, we decided to process the retweets separately.

Text Sentancing focuses on determining natural Opion of sentence within a corpus and is also known as unsupervised learning algorithms.Text summarization is extracting a summary automatically from a sentence uses elements of syntax and semantics. This is, by the way, an area of considerable interest to the military for discovering relevant documents in sentance. Author identification focuses on determining the author of a document where the author is either unknown or authorship is disputed. This task not only depends on the syntax and semantics found in the document, but also the characterizations of style of the document.

5.2 TRANSLATION ANALYSIS

Perhaps the most difficult task is automatic translation, which includes the morphology, the syntax, the semantics, and the lexicon of two languages. One reason translation is so difficult is that idiomatic expressions are hard to recognize and a literal translation may not make sense. Using multi-grams or strings of words to recognize idioms is a fruitful way to augment traditional translation techniques and one reason It have focused on these structures. Cross corpus discovery refers to comparison of documents for two or more corpora usually with the idea of finding similar or related documents.

5.2.1 EXPERIMENTAL RESULTS

The investigational revise has been performed on a ASUS – X550C laptop with an Intel Core i3-3217U, 1.8 GHz CPU, and with the RAM of 4GB, running in Windows 8.1. All programs are coded in JAVA. The following table explains the inputs and the outputs Polarity classification on social media analysis.

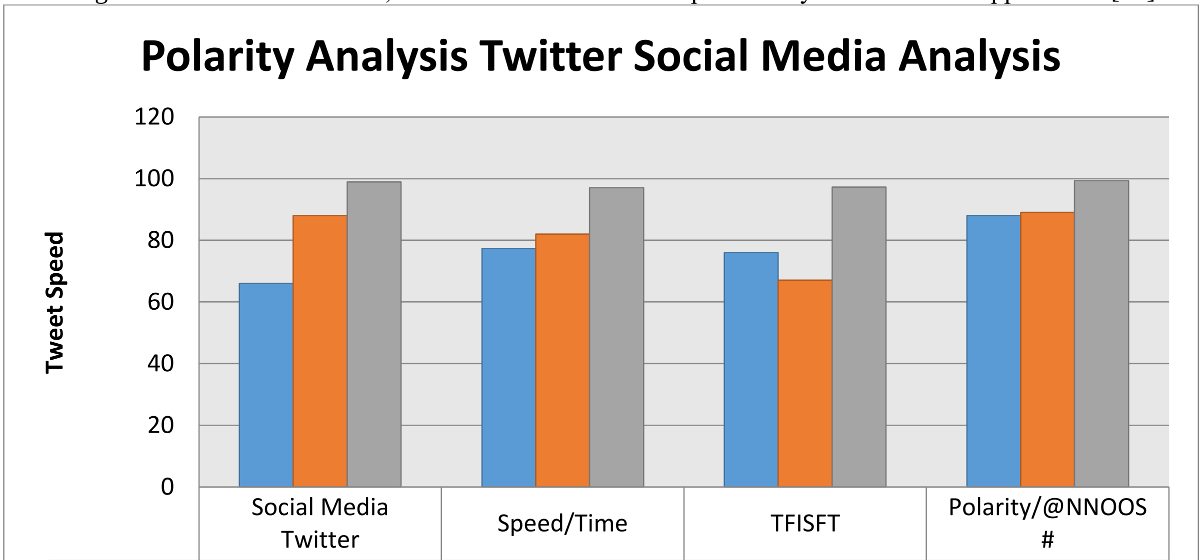
5.2.2 SENTENCE TEST ANALYSIS

Phonetics and phonology	The Analysis of language sounds
Ecology	The Analysis of language conventions for punctuation, text mark-up and encoding
Morphology	To Analysis meaningful components of words Hebrew (transliterated):ukshepagashtihu English:and when I met you (masculine)
Syntax	The Analysis of structural relationships among words
Lexical semantics	The Analysis of word meaning
Compositional semantics	The Analysis of the meaning of sentences
Pragmatics	TheAnalysis of the use of language to accomplish goals
Discourse conventions	The Analysis of conventions of dialogue
Tokenization	German:Lebensversicherungsgesellschaftsangesteller English:life insurance company employee

5.3 LEXICON:

Before launching on processing Sentence within a Uniform Resource Locator, it is usually advisable to do some preprocessing. These preprocessing steps usually reduce the size of the lexicon while preserving the semantic content of the documents in sentence.

5.3.1 COMPARATIVE STATEMENT ANALYSIS TIME: Two tasks are usually undertaken: denoising and stemming[13,14]. Denoising usually refers to removal of stopper words that have little semantic content[15]. Words such as the, an, and, of, by, that and other articles, conjunctions, or prepositions are likely be capable ofdidates for stopper words[17,18]. These are often just taken from a predetermined list. However, the stopper words may be corpus[9,19] dependent. **For example** in a corpus consisting of documents in sentence, words like "theorem" and "proof" may be treated as stopper words[20].

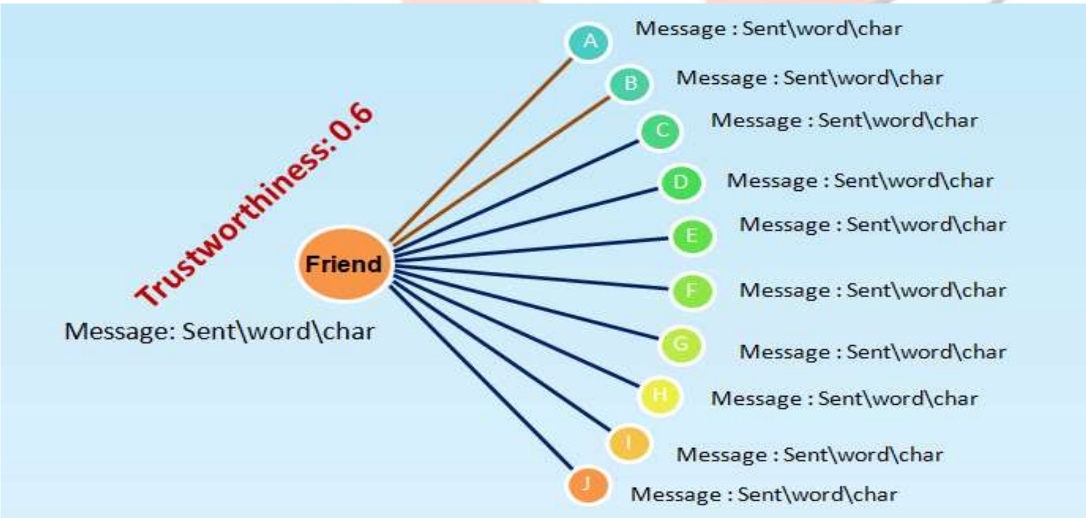


	Social Media Twitter	Speed/Time	TFISFT	Polarity/@NNOOS #
EM-2014	66	77.34	76.05	88
NB-2015	88	82.04	67.09	89.02
SVM-2016	98.9	97.1	97.23	99.34

5.4 FREQUENCY LOG INVERSE SENTANCE FREQUENCY TEXT(TFISFT):

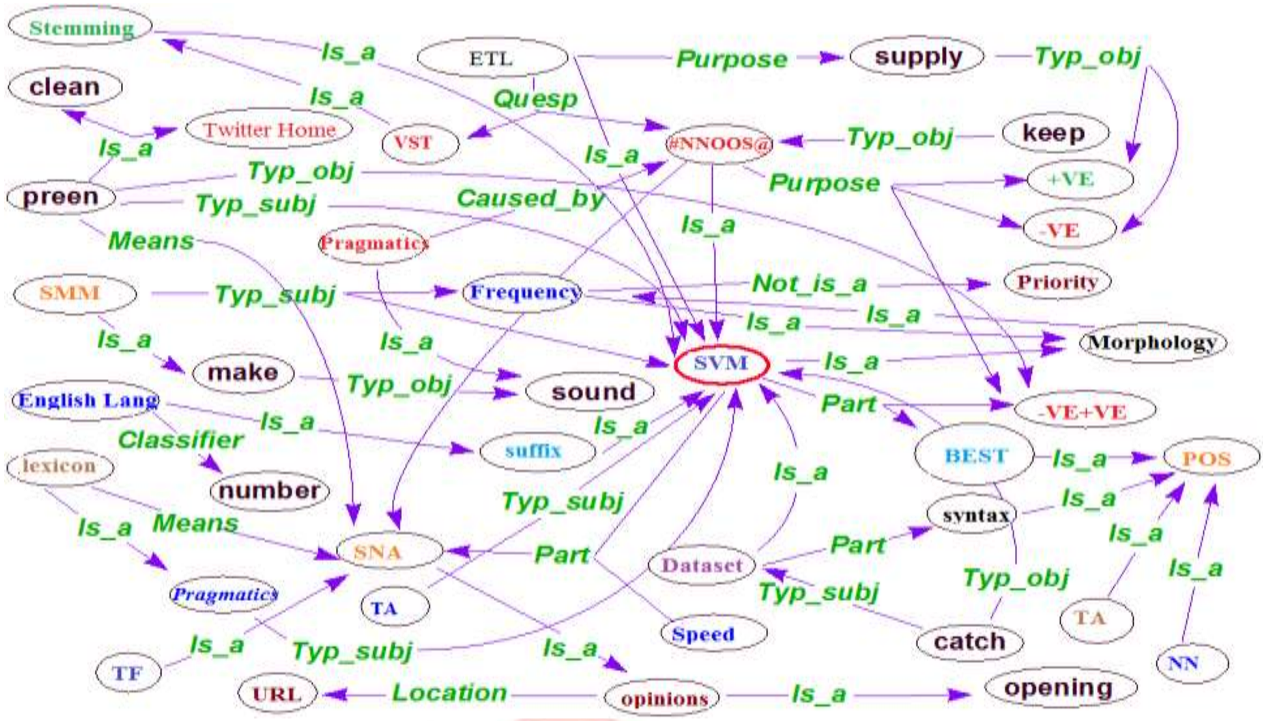
A way of automatically determining stopper words is to calculate the so-called Term Frequency Log Inverse Sentance Frequency Text(TFISFT). This measure down weights a word if it occurs infrequently in all of the documents of the corpus and also down weights a word that occurs in every document of the corpus. By thresholding on the so-called TFISFT measure, one be capable of automatically remove stopper words that are corpus dependent.

5.4.0 TFISFT



5.5 PREPROCESSING

Stemming is the other preprocessing step. This procedure removes suffixes, prefixes and infixes and is an attempt to replace words with their root. The example here replaces wake, waking, awake, woke with wake.There are perils with automated procedures as well. For example, browse (SPELL OUT), browsing, browsed, could conceivably be replaced with brows (SPELL OUT)[18]. so that a leisurely afternoon in a bookstore could become twitter message.



VI. 6.0 RESULT

Speed The original part-of-speech tagger processed about 16-19 tweets and 300 tokens per second, while the new version tags around 800 tweets and 20,000 tokens per second (7 million tweets/hour). Some of this improvement is due to algorithmic differences; see section 9. The tokenizer by itself runs at about 5500 tweets per second (14 million tweets/hour). Timings on an Intel Core i5 12.9 GHz laptop.

Figure 1 charts the number of positive, negative and neutral tweets over the entire collection.As readers may see, positive tweets—61% of the total—are more common than negative—16% of the total—or neutral ones—23% of the total.Both commercial and academic researchers have proposed a number of metrics to estimate the overall sentiment expressed towards particular topics on social networks. A common metric for this purpose is the Nutural sentiment rate (NSR) [10,15].The (NSR) is defined as the subtraction of the number of negative onversations—negative tweets in our case—from the number of positive conversations—positive tweets—divided by the total number of conversations—total number of tweets. In other words, NSR =Positive tweets _ Negative tweets/Total number o f tweets

Two basic types 1.Dictionary-based: uses lists of related words 2.Algorithmic: uses program to determine related words

6.1 ALGORITHMIC STEMMERS: *suffix-s:* remove 's' endings assuming plural.e.g., cats → cat, lakes → lake, wiis → wii . Many *false negatives*: supplies → supplie.Some *false positives*: ups → up.Generally a small but signifibe capable oft effectiveness improvement be capable of be crucial for some languages e.g., 5-10% improvement for English, up to 50% in any Language(Hindi,Tamil).

Social Media Analysis	Tweethood[1]	Tweecalization[2]	Twitter[3]	Content Based[4]
Positive(City)	72.1%	75.5%	86.3%	35.6% - 51%
Negative (Country)	80.1%	80.1%	94.9%	52.3%
Complexity	O(n)(worst)	$1(n^3)$(Average)	$O(n^3)$(Best)	N/A(Null)
SVM Temporal Analysis	No	No	Yes	Small Place

1.coach has 15 sentance 2. lose has 11 sentses.3.set has 91 words (15 x 11 x 91 = 15015) possible translations

6.2 STOPPING: Function words (determiners, prepositions) have little meaning on their own word high occurrence frequencies treated as *stopwords* (i.e. removed) reduce index space, improve response time, improve effectiveness Be capable of be important in combinations e.g., "to be or not to be" Stopword list be capable of be created from high-frequency words or based on a standard list Lists are customized for applications, domains, and even parts of Sentence e.g., "click" is a good stopword for anchor text best policy is to index all words in documents, make decisions about which words to use at query time.

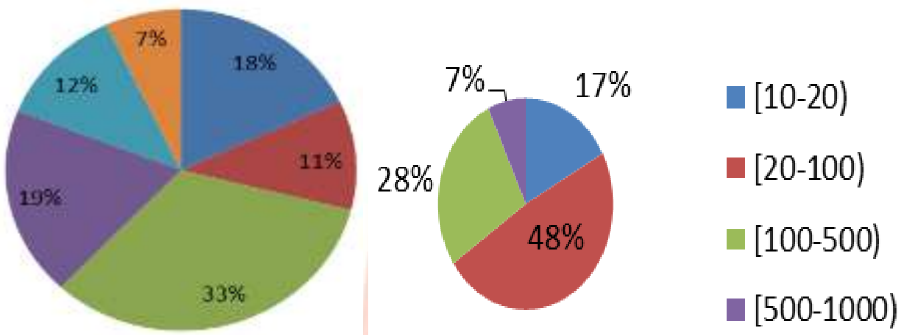
6.2.1 TEST ANALYSIS OTHER LANGAGE:

Relatively simple for English. But for some languages such as Turkish, it is more difficult.**uygarlaştıramadıklarımızdanmışsınızcasına**.uygar-laş-tır-ama-dık-lar-ımız-dan-mış-sınız-casına.uygar +BEC +CAUS +NEGABLE +PPART +PL +P1PL +ABL +PAST +2PL +AsIf. "(behaving) as if you are among those whom It could not civilize/cause to become civilized".

+BEC	is"become" in English
+CAUS	is the causative voice marker on a verb
+PPART	marks a past participle form
+P1PL is	1st person plural possessive marker
+2PL	is 2nd person plural
+ABL	is the ablative (from/among) case marker
+As	If is a derivational marker that forms an adverb from a finite verb f
+NEGABLE	is "not able" in English

Inflectional and Derivational Morphology. Common tools: Finite-state transducers

6.3 LINGUISTIC DATA CONSORTIUM:



In order to illustrate the dimension and scale of the vector space[7,8] methods,In this using a subset of the text data that were collected by the Linguistic Data Consortium in 2015.These data were originally used in Martinez (2016). The data consisted of 15,863 news reports collected from Reuters and CNET from July 1, 2015 to June 30, 2016. The full lexicon for the text database included 68,354 distinct words. In all 313 stopper words are removed and after denoising and stemming, there remain 45,021 words in the lexicon.In the examples that I report here, there are 503 documents only. Even the 503 document database proves to be challenging. The 503 document corpus that It have worked with has 7,143 entries in its lexicon and 91,709 bigrams.

6.4 TERM FREQUENCY TEXT MINING VS FREQUENCY TEXT ANALYSIS:

Thus, the TFTM is 7,143 by 503 and the FTA is 91,709 by 503.The term vector is 7,143Sentance of words and the bigram vector is 91,709 Sentance of words .The FTA for each document is 91,709 by 91,709 and very sparse.A corpus be capable of easily reach 20,000 documents or more and scaling is a signifibe capable oft issue in text processing. I begin the analysis of the 503 documents by considering the term frequency. The top graphic illustrates the term count for each of the documents in the ordered by their frequency count. The frequency count appears to follow a power law. The graphic is a zoomed version showing the top 187 words, in particular, those words that have a frequency count of 150 or more. Interestingly enough the most frequently appearing word is "say" while "said" comes in sixth. The word "think" comes in 20th. One has always suspected that politicians talk more than they think. This is the graph theoretic representation of the term-document Sentance of words with 503 documents and the top 255 terms. Already by this relatively modest corpus the SVM algorithms is a hopeless and of course the adjacency matrix will contain 17,500 entries.

VII. 7.0 CONCLUSION:

Experiment showed signifibe capable oft improvements from using unlabeled documents of sentence words in letter one by one analysis for training classifiers in three real-world text classification tasks.Using unlabeled data requires a closer match between the data and the model than those using only labeled data. Warrants exploring more complex mixture models. Lexical Resources have been developed to capture sentiment-related nature.SVM extracts provide a better Speed of sentiment prediction.Several approaches use algorithms like SVM, Sentanceing to perform sentiment analysis.

VIII. 8.0 REFERENCE

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