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Lexicon-Based Sentiment Analysis in the Social Web

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ABSTRACT

Sentiment analysis is a compelling issue for both information producers and consumers. We are living in the "age of customer", where customer knowledge and perception is a key for running successful business. The goal of sentiment analysis is to recognize and express emotions digitally. This paper presents the lexicon-based framework for sentiment classification, which classifies tweets as a positive, negative, or neutral. The proposed framework also detects and scores the slangs used in the tweets. The comparative results show that the proposed system outperforms the existing systems. It achieves 92% accuracy in binary classification and 87% in multi-class classification.
KEYWORDS: Opinion Mining, Lexicon, Tweets, Social media, Semantic Orientation

I. INTRODUCTION

The information age has created great opportunities and challenges for business community, consumers, tourists, politicians, government, and general public [1,2,3,4]. Mountains of online data are generated every day with unprecedented speed and size. Most of the available information on Internet is in text and unstructured form [5]. This type of information is continuously increasing with flood of online reviews, blogs, chat, and news. Social media networking such as Facebook, Twitter, Youtube, MySpace, and LinkedIn are the major contributors to this overwhelming data. Social media sites are increasingly used by the users to connect and share sentiments related to events and products, anytime from anywhere. A social media site Twitter users sent 25 billion Tweets in 12 months [6]. Study [7] shows that 80% of consumers have changed their decision about their purchasing based on negative reviews they found on Web. Due to the popularity of these social media sites, it is not possible to ignore this fastest growing communication mechanism among the Web users. People post real time messages almost in every field of life containing opinions and thoughts, which is the rich source for Opinion Mining, and Sentiment Analysis [8]. Opinion Mining and Sentiment Analysis is the application of Natural Language Processing (NLP) techniques to get the subjective information from the source text [9].

This paper is concerned with the analysis of Twitter messages called tweets. Twitter is a popular Social networking and microblogging service to send text-based messages (tweets) up to 140 characters [10,11]. Sentiment analysis over tweets are performed differently compared to other lengthy plain text messages. This constraint is due to short length, uses of slangs, abbreviations and poor structure of sentences in the tweets, which makes it more difficult to analyze the text. There are two major approaches for automatic extraction of sentiments from the target text i.e. lexicon-based method and the text classification method [12]. In the first approach semantic orientation (SO) of the document is calculated by summing the SO of the words and phrases in the document [13]. In the second approach classifier is built from the annotated instances of the text or sentences [14]. We follow the first approach (lexicon-based) in this paper. Our framework is based on the integration of different lexicons and dictionary resources. The experiment shows that our results are comparable with the existing approaches.

The rest of the paper is organized as follows. Related work is described in the next section II, followed by the proposed framework and experimental setup in section III and IV. Section V and VI discuss the results and conclusion respectively.

II. RELATED WORK

The term sentiment analysis appeared in [16] work, and the term opinion mining appeared in [17] for the first time. However the research in the field of sentiment analysis started with products [13] and movie [14], which was closely related to predicting SO of adjectives [18]. Point Mutual Information (PMI) is used in [13] to estimate the sentiment orientation of phrases. Supervised learning with various set of n-gram features is used in [14] achieving an accuracy of 83% with unigram for binary sentiment classification of documents. Later the sentiment analysis research extended to other domains including blogs and news [19,20]. Most of the early research work done, on

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longer documents, including movie reviews and blogs. Researchers tested the hypothesis [21] that classifying the sentiment in short document is easier than longer one, but difficult to improve the performance of sentiment classification in micro text.

Positive and negative emoticons, and hashtags in tweets were studied in [22,28] as a representative for sentiment labels. The blogs, a rapidly growing way of communication is a rich source for sentiment analysis [23,24]. Bloggers express their feeling, emotions toward different entities [25]. Most of the blogs contain comments, reviews on products, events, or services [26].

Microblogging services data is an ample source for opinion mining researchers. Twitter and other microblogging services act as a platform for marketing and social relations [27]. Classification of tweets as a positive or negative by emoticons are studied in [28]. Sentiment analysis tasks can be classified on the basis of their using levels, i.e. word level, sentence level, document level, and feature level [29]. Sentiment analysis at word level properly fits for tweets. Although Twitter messages do not follow strict rules of language grammar, contains variety of symbols, abbreviations, and incomplete sentences. The above complexities result a different vocabulary, and challenges for researchers to mine tweets for sentiment. The simplest solution for sentiment analysis is of using “bag of words” model, which simplifies information retrieval and text mining [30], but it does not preserve the order of words in the sentences [57].

There are two major approaches used by the researchers to extract sentiment from text automatically i.e. lexicon-based and text classification approach [12]. In the first case documents SO is calculated from the words or phrases SO [13]. In the second case classifiers are built from annotated instances of text or sentences also described as a statistical or machine learning approach [14,15]. Supervised machine learning methods based classifiers have gained high accuracy in detection of text polarity [31], but performance of machine learning is domain dependent [32]. On the other hand lexicon-based approach works well in cross-domain and can be enhanced easily with source of additional knowledge for sentiment classification [33]. Lexicon-based approach also performs well in handling contextual valence shifter [12], blog posting and video game review [34,35].

Dictionaries are created manually or automatically for lexicon-based approach [36]. Most of the lexicon-based approach uses adjective as a SO indicator. SO values are compiled into a dictionary. Then all adjectives are extracted from the target text, and labeled with their SO value using the dictionary. Lexicon-based scoring of tweets using the R approach is studied in [37], however their work is based on simple average sentiment score. A hybrid approach is adopted in [38] to classify the tweets into positive, negative, and neutral. They presented a case study to show the effectiveness of the system, but they did not address the slangs in sentiment classification. Limited work is carried out on analysis of Internet Slangs for sentiment analysis [39].

Majority of the work in sentiment analysis is based on binary classification i.e. dividing reviews or blogs into “positive” and “negative” classes [40,41]. This research work follows the lexicon-based approach, which integrates different lexicons and dictionary resources for sentiment classification of tweets. Extracting and scoring of slangs and abbreviations used in tweets [58] is also part of this research work. Result is presented as positive, negative or neutral.

III. PROPOSED FRAMEWORK

The **proposed Lexicon-based Sentiment Analysis in the Social Web (LBSASW)** framework for sentiment classification is depicted in Figure 1. It consists of six major modules.

Tweets Capturing Module

This is the first module of our framework, and programmed in Python programming language. Python package called Tweepy, which provides simplified access to streaming API resources, was used. All downloaded tweets were stored in SQL Server 2012 database for further processing.

Preprocessing Module

This module performs various preprocessing tasks as explained in section IV.

Lexicon Module

Lexicon module integrates different opinion lexicons, and dictionary resources. It provides foundation for our framework. The introduction of each individual component in this module is given in section IV.

Subjective Text Identification

This module performs two tasks: (i) Extracting opinionated word from the source text (ii) Slangs detection and translation.

Additional Knowledge Module

This module is used to acquire the additional knowledge to enhance the stop-words list, lexicons, and slangs detection process.

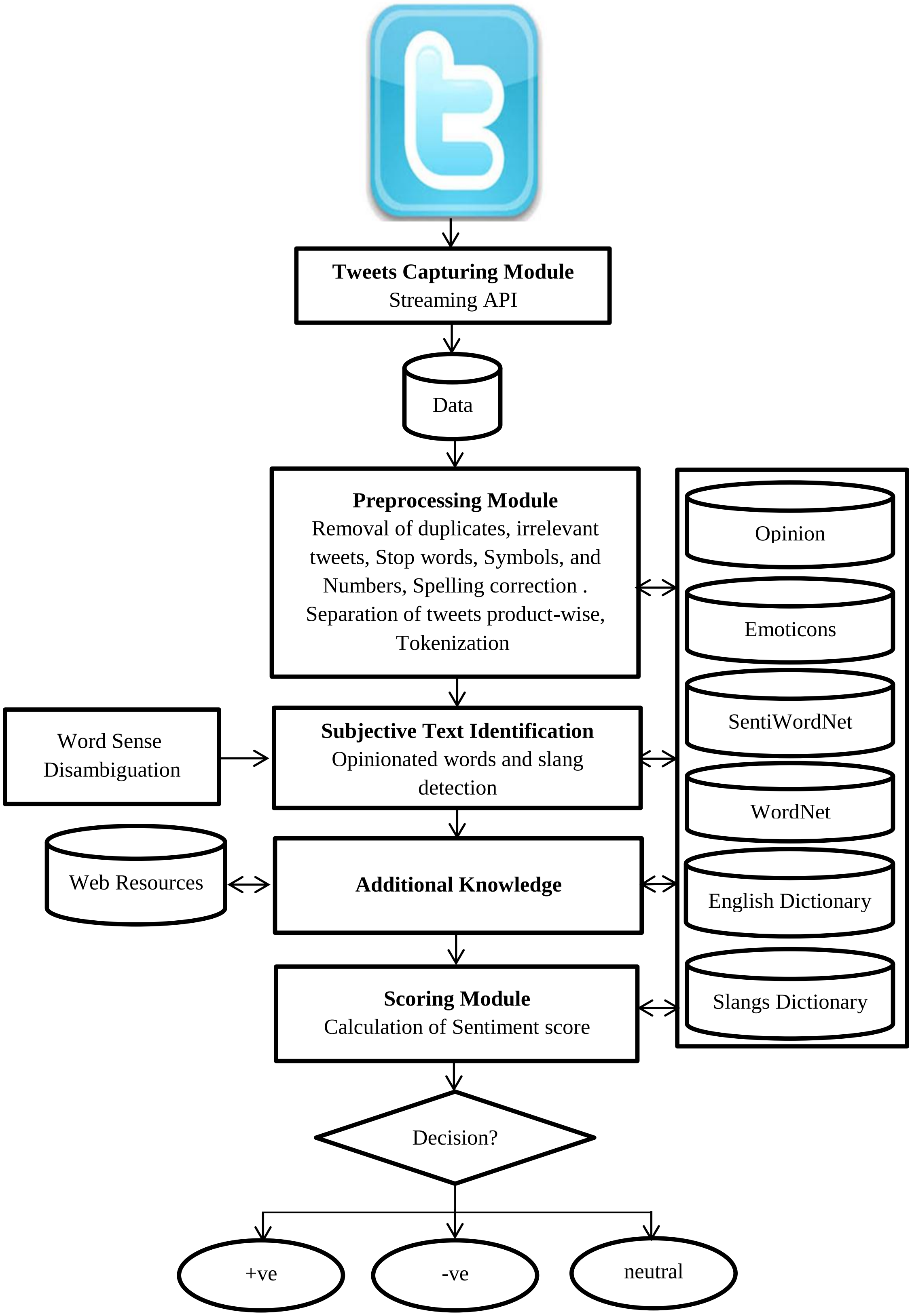

Figure 1. System Framework

Input: Tweets/Reviews
Output: Sentiment Score
NL: Negations List
IL: Intensifiers List

```
Function Senti_Score(tweet)
    ptext = preprocessor(tweet)
    tokens = tokenize(ptext)
    ## Tasks
    ## (i) If word is in NL then reverse polarity of word+1
    ## (ii) If word is in IL then modify polarity of word+1
    ## (iii) If all letters in the word are in upper case then add fraction to word score
    ## (iv) Enhance word score if it contains repeated letters
    ## Exclamation count
    Xc = exclam(ptext)
    For word in tokens
        If word in emoticons Then
            score = emoticon score
        Else
        ## Searching opinion lexicons/dictionaries
            If word found in lexicon assign score.
                score = lexicon score
                do task (i) to (iv)
            If word not found, check its synonyms and antonyms and assign score.
                score = lexicon score
                do task (i) to (iv)
            If not found, check in SentiWordNet  and calculate its score.
                score = SentiWordNet score
                do task (i) to (iv)
            If not found in SentiWordNet, search Slang's dictionary/Web and calculate its score.
                score = Slang's score
            If not found,  assign score zero
                score = 0
        EndIf
        tweetscore = tweetscore + score
    Next
    score = (Xc+1)/2* tweetscore
End Function
```

Figure 2. Algorithm for Sentiment Scoring

Scoring Module

Scoring module classifies the tweets into positive, negative, or neutral. It consists of several sub-modules: Scoring words, slangs, handling of synonyms, antonyms, negations, intensifiers, singular and plural forms. In the first step we assign +1 to each positive word and -1 to each negative word in the lexicon. Emoticons were compiled into list of positive and negative assigning score of +1 and -1 to each positive and negative emoticon respectively. If the given word is not found in the lexicon or emonticons list then sentiment score is calculated using SentiWordNet (SWN). SWN associates three numerical values with each synset of Wordnet i.e. *pos(w)* , *neg(w)* and *obj(w)*. Sum of all three values is unity, therefore objective score can be calculated as follow:

$$obj(w) = 1 - [pos(w) + neg(w)] \quad (1)$$

Each entry in SWN has multiple senses. Average of *pos(w)* , *neg(w)* and *obj(w)* scores for each sense is calculated according to the part of speech (POS) as shown in Eq. (2), (3) and (4). If *obj(w)* score is less then threshold value (0.5) the word is considered as a positive or negative otherwise it is objective and score zero is assigned. Positive or negative difference between *pos(w)* and *neg(w)* indicates word positivity or negativity.

$$pos\_score(w) = \sum_{i=1}^{n} pos(p_i)/n \quad (2)$$

$$neg\_score(w) = \sum_{i=1}^{n} neg(p_i)/n \quad (3)$$

$$obj\_score(w) = \sum_{i=1}^{n} obj(p_i)/n \quad (4)$$

Where *pos_score(w), neg_score(w)* and *obj_score(w)* represent positive, negative and objective semantic score of all synsets for word *w*, p_i is the polarity score of *ith* synset and *n* is the total number of synsets. The overall sentiment score formula and its components are shown below.

$$Score(S_i) = W_{S_i} + E_{S_i} + S_{S_i} + L_{R_i} \quad (5)$$

$$S_{S_i} = [\ (pos\_score(S_{S_i}) + pf) - (neg\_score(S_{S_i}) + nf)] \quad (6)$$

Where W_{Si}, E_{Si} and S_{Si} represent score of *ith* word, emoticon and slang respectively. L_{Ri} is the number of repeated letters in the *ith* word. The term *pf* and *nf* represent the fraction of positive and negative documents respectively that contain the given slang. The complete formula for calculating the sentiment of entire document is shown in Eq. (7).

$$Score(tweet) = \frac{(1+X_c)}{2} * \sum_{i=1}^{|t|} Score(S_i) \quad (7)$$

Where $X_c$is the number of exclamations in the tweet and |t| is the length (number of tokens) of tweet. Sentiment scoring algorithm is shown in figure 2.

IV. EXPERIMENTAL SETUP

This section presents the complete experimental setup for our work i.e. lexical resources, data set, preprocessing, and performance evaluation.

Lexical Resources Used

There are two major approaches for automatic extraction of sentiments from the target text i.e. lexicon-based method and the text classification method. In the first approach semantic orientation of the document is calculated by summing the SO of the words and phrases in the document. In the second approach classifier is built from the annotated instances of the text or sentences [12,13,14]. The lexicon-based approach works well in cross-domain and can be enhanced easily with source of additional knowledge for sentiment classification [33]. We follow the first approach in this research work. Our approach is based of integration of various lexicons and dictionary resources for sentiment. Following lexicons and dictionaries are used in our work:

General Purpose Opinion Lexicon

This general purpose opinion lexicon [42] (referred as Lexicon-1) contains 1967 positive and 4783 negative sentiment words. Some misspelled words are also included in the lexicon as they appear frequently in the social media text.

Dadvar Opinion Lexicon

This Dadvar Opinion Lexicon [43] (referred as Lexicon-2) is of small size, which contains 136 positive, and 109 negative sentiment words.

Emoticons Dictionary

We compile 100 emoticons dictionary found at Wikipedia[44] by labeling them as a positive or negative. Score 1 is assigned to positive and -1 to negative emoticon.

Wordnet

Wordnet [45] is a lexical repository for English language. It is comprised of 155,287 words and 117,659 synsets, also called synonyms**.**

SentiWordNet

Sentiwordnet [46] is a lexical resource and an extension of Wordnet. It associates each Wordnet synset with three numerical scores i.e. positive, negative, and objective. These scores range from 0.0 to 1.0, and sum of scores for each synset is 1.

English Dictionary

This English dictionary [47] contains 79768 words. The purpose of this dictionary in our work is word validation and spelling correction, if not found in other lexicons.

Slang Dictionary

More than 5000 slangs (acronyms) are collected from the web[48] and compiled with their translation for scoring.

Urban Dictionary

Urban dictionary[49]is web-based dictionary founded in 1999, which contains more than seven million definitions. It is one of the best site among social media users. Our slang's detection and translation process ends at Urban dictionary. It is ignored if not found in the Urban dictionary.

Dataset

The original unprocessed data set used in this research work contains 308316 tweets for three products (iPhone, Nokia, Samsung), which were collected from 10 April 2013 to 11 April 2013 using Twitter streaming API. Python package Tweepy was used, which provides the simplified access to streaming API resources. Non-English and retweets are ignored. Table 1 shows the statistics of tweets dataset. For annotation 1300 tweets were distributed among university students registered in data mining course. All tweets are labeled as positive, negative, or neutral. After reviewing, tweets were classified by the proposed framework.

Table 1. Statistics of tweets

Total# of tweets	**308316**
Retweet	47017
English tweet	151347
Manually Labeled tweets	1300
iPhone	46%
Nokia	24%
Samsung	30%

Preprocessing

Preprocessing is the important step in data mining. To avoid incorrect and misleading results, data must be pre-processed before analysis [50,51]. Twitter users use variety of symbols, abbreviations, and non-standard language in their tweets. The collected tweets for this research work were pre-processed in the following way.

- Irrelevant tweets (non-English) are removed from the data set.
- Duplicate of any tweet are deleted from the data set.
- Stop words, numeric expressions and punctuations are removed. Repeated spaces are replaced with single space character. Characters repeated 2 or more times in any word are replaced with one or two occurrences for spelling correction if possible. Repeated characters are normally used to emphasize.
- Words with all capital letters are identified used for expressing powerful emotions.
- Hash tags (#) and RT (retweet) symbols are removed.
- All tokens starting with "http://", "https://", "http:", "http", or "www." are replaced with <URL>.
- Negations "don't", "didn't" etc. are replaced with "do-not", "did-not" before tokenization, to simplifying the text analysis.
- @username is replaced with <AT-USER>.

Table 2 shows the set of emoticons detected in corpus. The emoticons :) and :(have highest rank in the corpus.

Table 2. Set of emoticons

Positive	**Negative**
:) :-) :D :p ;) ;-) ;D ;p =) =D XD ^-^	:(:-(;(;-(=(:o

Performance Evaluation

Confusion matrix [52] also called contingency table or error matrix is used to present the result of classifier for prediction. It is a special table to visualize performance of the model. Table 3 shows the confusion matrix for binary classification. Researchers use various performance measures to evaluate the performance of classifier including precision, recall, F-score, and Matthew correlation coefficient (MCC).

Table 3. Confusion Matrix for Binary Classification

		Machine Says	
		Positive	**Negative**
Human Says	**Positive**	TP	FN
	Negative	FP	TN

True Positive (TP): Number of positive tweets classified correctly.
False Positive (FP): Number of negative tweets classified incorrectly as a positive.
True Negative (TN): Number of negative tweets classified correctly.
False Negative (FN): Number of positive tweets classified incorrectly as a negative.

Precision

Precision [53] also called positive predicted value, measures the correctness of the model. Higher precision indicates less FP. Mathematically it is defined as:

$$Precision\,, p = \frac{TP}{TP+FP} \tag{8}$$

Recall

Recall [53] also known as sensitivity, measures positive cases correctly classified by the model, large recall value means few positive cases misclassified as a negative. Recall can be calculated using the following formula.

$$Recall, r = \frac{TP}{TP+FN} \tag{9}$$

F-Score

F-score or F1-measure [53] is the harmonic mean of precision and recall. F-score can be calculated as follow:

$$F - Score = \frac{2rp}{r+p} = \frac{2TP}{2TP+Fp+FN} \tag{10}$$

False Positive Rate (FPR)

FPR or false alarm ratio measures the cases classified as positive incorrectly [53]. It is calculated as follow:

$$False\ Positive\ Rate, fpr = \frac{FP}{FP+TN} \tag{11}$$

Matthews Correlation Coefficient

MCC[54] is used to measure the quality of binary classification. It is based on true and false, positives and negatives. Value of MCC lies between -1 and +1. A coefficient of +1 represents perfect prediction, 0 indicates completely random prediction, and -1 indicates no relationship between saying of human and machine. MCC can be calculated as follow:

$$MCC = \frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{12}$$

V. RESULTS AND DISCUSSION

We performed experiments on two types of sentiment classification i.e. positive versus negative and positive versus negative versus neutral. In the first phase various lexicons were used for sentiment analysis of tweets following simple scoring approach [37] to show that accuracy is directly related to the size of lexicon and its coverage. Table 4 shows the result for positive versus negative Sentiment classification.

Table 4. Simple Scoring Accuracy in Positive versus Negative

Lexicon	Accuracy
Lexicon-1	0.6308
Lexicon-2	0.3154
Emoticons	0.3385
Hybrid-1	0.7385
Hybrid-2	0.5077
SentiWordNet	0.7077

The above results show that Lexicon-1 has higher accuracy then Lexicon-2 because of its more coverage of sentiment words. Emoticons are widely used in online reviews and tweets. In Hybrid-1 (Lexicon-1 + Emoticons) approach accuracy jumps from 63% to 74%. In the second phase of the experiment Lexicon-based integrated approach is used for binary classification (positive versus negative) and multi-class classification (positive versus negative versus neutral). Table 5 and Table 6 show the results of second phase.

Table 5. Binary Classification Performance

Measure	Result		
	Overall	Positive	Negative
Accuracy	0.9154	0.8977	0.9524
Precision	0.9753	0.9753	0.8163
Recall	0.8977	0.8977	0.9524
F-Score	0.9349	0.9349	0.8791
TNR	0.9524		
FPR	0.0476		
MCC	0.8204		

Table 6. Multi-class Classification Performance
W/S: With Slangs, WO/S: Without Slangs

Measure	Result							
	Overall		Positive		Negative		Neutral	
	W/S	WO/S	W/S	WO/S	W/S	WO/S	W/S	WO/S
Accuracy	0.8733	0.8467	0.8864	0.8523	0.9524	0.9286	0.65	0.65
Precision			0.9750	0.9740	0.7407	0.7222	0.8125	0.6842
Recall			0.8864	0.8523	0.9523	0.9286	0.65	0.65
F-Score			0.9286	0.9091	0.8333	0.8125	0.7222	0.6667

The Table 5 shows the overall accuracy of 92% for binary sentiment classification. The false positive rate is only 5%. MCC for binary classification is 0.8204, which indicates the good prediction. For multi-class overall accuracy is 87%, where for positive and negative are 88% and 95% respectively. High precision for positive means less false positive. Multi-class classification performed with and without slangs. The result shows that slangs has great impact on the accuracy of sentiment classification. Table 7 and table 8 present comparative performance. Sample of tweets with their sentiment score and orientation are shown in table 9.

Table 7. Binary Classification Comparative Performance

	Method	Precision	Recall	F-Score
Positive	[41]	0.94	0.86	0.90
	[55]	0.81	0.82	0.81
	This Study	**0.98**	**0.90**	**0.93**
Negative	[41]	**0.88**	**0.95**	**0.91**
	[55]	0.85	0.78	0.81
	This Study	0.82	**0.95**	0.88

Table 8. Multi-class Classification Comparative Performance

	Method	Precision	Recall	F-Score
Positive	[56]	0.54	0.65	0.59
	This Study	**0.98**	**0.89**	**0.93**
Negative	[56]	0.61	0.43	0.51
	This Study	**0.74**	**0.95**	**0.65**
Neutral	[56]	0.77	**0.77**	**0.77**
	This Study	**0.81**	0.65	0.72

Table 9. Tweets Sentiment Score with Semantic Orientation

Tweet	Score	Orientation
@bellathorne If I see a picture on my iPhone that says Bella follows you will get a big smile on my lip :)	2.0	Positive
iPhone batteries are actually so fucking shitty Been without a phone all day & night	-1.475	Negative
I came home from practice and my mommy brought me Chipotle :-) :-) :-) :-) she so gr8	2.62907	Positive
Your eyes is colorfull like #WarnaWarniGalaxy, that is why I falling in love with you :) :) cc. @Samsung_ID	2.072917	Positive
Chale :(jodido iOS 7 en México #iOS7 #ios7mexico #fail #iphone4mexico	-1.01515	Negative
iPhone of Samsung - http://t co/501s9dBS3m	0	Neutral
Pregnancy week to week: Pregnancy week to weekCategory: Released: 2013-04-10 04:35:01Price: 0 http://t co/KITPmwmbM9 - iPhone App	0	Neutral

VI. CONCLUSION AND FUTURE WORK

In this paper we developed a framework for sentiment classification by integration of lexicons and dictionaries. We achieved 92% accuracy in binary classification and 87% in multi-class classification. The system needs to improve the precision in negative cases and recall in neutral cases. In the future, we plan to expand this framework by testing with other datasets.

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