Sentiment Analysis and Opinion Mining - A Facebook Posts and Comments Analyzer

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Abstract-Since last few years, the trend of social networking is at its peak. People post their personal feelings and thinking about any topic or product for social liking or for marketing. Such posts often get hundreds or thousands of comments and it becomes difficult for a reader to read all of these to assess public opinion. Sometimes one just wants to know common opinion, behavior, trend or thinking discussed there or to determine whether those opinions are positive or negative. Particularly in case of product marketing, the company would like to judge the success of an ad campaign or new product launch or which products or services are popular and what people like or dislike about particular features of a product. In such situations automatic sentiment analysis and opinion mining can help a lot. Hence, in this paper a novel sentiment analysis and opinion mining framework is proposed. This framework utilizes various techniques of computational linguistics to measure sentiment orientation of user's opinion around different entities. The proposed framework is used to perform sentiment analysis and opinion mining of users' posts and comments on social media through a Facebook App. Furthermore a user study is conducted to gauge performance of the proposed framework. The results of this study have shown that the framework is capable of finding opinions of the users and sentiments around those opinions with more than 85 percent accuracy when compared with actual human judges.

Keywords-Sentiment Analysis, Opinion Mining, Comments Analyzer, Facebook

I. INTRODUCTION

With the advent of Web 2.0 now web is not a read only media anymore. Beside consuming information on Web now users can also contribute into it through comments, blogs, feedback etc. which has changed the way we consume and produce information. Online social media is among the paramount examples of those applications which have been realized through Web 2.0. Now, on an online social media platform people post their personal finding, feeling or thinking about any topic or a product for social communication, branding, marketing etc. A popular User's or Company's post usually attract hundreds or thousands of comments and it looks difficult for a reader to read all of these comments to assess general public opinion about the topic discussed in the post. Furthermore, in case of marketing, one may like to judge the success of an ad campaign or new product launch or which products or services are popular and what people like or dislike about a particular feature of that product [i]. In such situations automatic sentiment analysis and opinion mining can help a lot. The purpose of sentiment analysis from a set of comments is to determine the attitude of commenters with respect to some subtopic or their overall contextual polarity towards the topic. This attitude may be their actual evaluation or can be caused by any emotional communication [ii].

Recently, a tremendous focus has been observed in literature to design new techniques to meet different requirements of the sentiment analysis and mining of writer's opinion [iii]-[v]. In [vi] a rule based approach is proposed to analyze sentiments through association rule mining for opinion extraction related to different product features. Such techniques has been used in several application areas including product feature extraction, summarization and analysis [vii]-[ix], e-commerce [x], tourism [xi], recommender system [x-xi] etc. Detailed literature review of sentiment analysis and its applications could be found in [iii-iv].

In this paper, a framework is designed through which opinions from reviews of people and sentiments (positivity or negativity) around those opinions could be found. The proposed framework is applied and realized as an application in which opinion mining and sentiment analysis of Facebook posts and comments of those posts are determined. This application helps users to understand the sentiments discussed in a post, extracts the topics with their semantics and also brings up the entities which are under discussion by the reviewers. Moreover, trend and behavior of reviewers can also be judged through the comment with its polarity with topics and entities. To evaluate proposed effectiveness of the design application based on the proposed framework a user study is performed which has shown very promising results.

Rest of the paper is organized as follows, in section

II some background of various techniques used are described, details of proposed methodology and its implementation is presented in section III and IV while in section V user experiments and results are reported. Finally section VI carries a discussion with the future work.

II. BACKGROUND

Sentiment analysis and opinion mining due to its social and commercial value has become a very hot topic of research these days. On other hand online social media has become a most significant mode of communication on Web 2.0. Hence sentiment analysis and user opinion mining on online social media has a great social and commercial importance. On social media for sentiment analysis twitter due to is simplicity has remained primary focus of researcher [xiv]-[xviii] while Facebook has been less addressed. Hence in this study a framework is proposed to analyze Facebook posts and comments for opinions and sentiments of the public.

Approaches used in literature for sentiment analysis and opinion mining are primarily based on three types which include machine learning, Lexicon and hybrid [iii], [xix]. Machine learning based approaches mainly use supervised learning [xix], [xx] where a piece of text is compared with human developed list of sentiment bearing words. In this approach an overall scores (more or less positive, negative or neutral) is assigned to the text based on the human designed list. This technique works better for short informal text where people are less formal in using grammar, which is the case in the people comments on the Facebook.

Second type of techniques [xxi] are based on proper grammatical check on the text using various methods of Natural Language Processing. These techniques are mandatory for text where proper grammar has been used. Finally, Hybrid techniques use combination of above mentioned and related techniques for sentiment analysis and opinion mining. For example in [xxii] a hybrid technique of opinion mining for e-commerce applications is proposed which is a combination of principal component analysis for feature reduction and supervised machine learning for prediction of opinions.

As the current study is focused on the sentiment analysis and opinion mining from the text of online social media namely Facebook and the text on Facebook carries formal as well as informal text expressions, hence the proposed framework is based on a hybrid technique. In the proposed framework, both machine learning based technique as well as natural language processing based techniques are used.

III. METHODOLOGY

Sentiment analysis is the process of detecting whether a chunk of text carries positive, negative or neutral feelings. Humans have their natural ability to find out sentiments. Human based sentiment analysis and opinion mining bears some limitations described as follows

a) un-scalable
b) can consume huge amount of time
c) un-suitable for real-time decision making
d) very time consuming
e) may be inconsistent if reviewed by different human

In order to deal with these limitation of human beings, a computational framework for sentiment analysis and opinion mining is proposed, in this work. Primary flow and functionality of the proposed framework has been shown in Fig. 1.

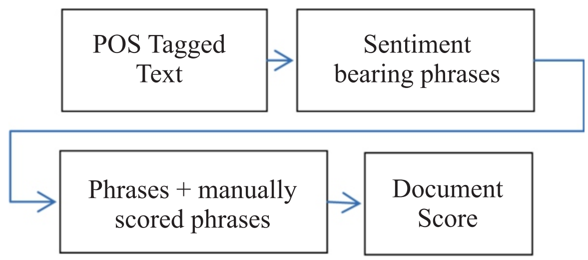

Fig. 1. Framework for Opinion and Sentiment Mining

The framework presented in Fig. 1 is capable of extracting sentiments from a text data set and the entities around which these sentiments are generated. Following are the core steps proposed in the framework which leads to get sentiment orientation of text around entities in a text data set.

In first step all sentences of the text documents are broken into its Parts of Speech (POS), which detects the elements of a document depending upon its grammatical structure (e.g. nouns, adjectives, verbs, and adverbs etc.). Then the rule base expressed in Table I is used to identify Sentiment Orientation (SO) in the text. The SO is determined by identifying whether bigram words are mutually independent or not. For example in phrase "beautiful flower", first word in a bigram is adjective while second is a noun. These two words are mutually dependent as expressed in first row of the Table I.

TABLE I
RULE BASE FOR IDENTIFICATION OF SENTIMENT ORIENTATION (SO)

First Word	Second Word	Third Word (not extracted)
Adjective	Noun	Anything
Adverb	Adjective	Not Noun
Adjective	Adjective	Not Noun
Noun	Adjective	Not Noun
Adverb	Verb	Anything

After identifying sentiment orientation in the text, pre-tagged sentiment lexicons are used to compare with text documents to determine sentiment-bearing phrases. In Social media some phrases also bear Emoticons. To determine sentiment orientation of Emoticons phrases, pre-coded emoticon sentiments are used for example smiley is coded as positive sentiment. Emoticon phrases are of higher precedence among others i.e., with respect to sentiment-bearing phrases. Finally, each phrase polarity is combined to determine the eventual polarity of a sentence and entities in those sentences.

To determine that the sentiments of sentences calculated above are associated with which entity Named Entity Extraction (NEE) is performed. For NEE proper nouns from text are pulled out such as people, places and institutions from text data set. NEE provides valuable inside from text, like what people are talking about for example a company, more importantly what they are talking about that company, to avoid initial training by user, a sentence is checked by its grammar (Parts of Speech) tag. To improve accuracy of NEE a list of named entities is populated through Wikipedia data set this pre compiled list of named entities is used through which this framework has supported extraction of entities remarkably well. In Fig. 2, the basic process through which named entities are extracted from a piece of text is shown.

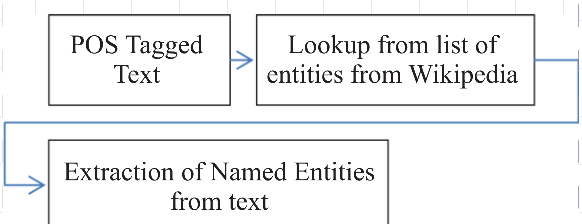

Fig. 2. Process for Named Entity Extraction

After performing above two steps as depicted in Fig. 1 and Fig. 2 the proposed framework is capable of determining sentiment orientation of phrases and the entities with which these sentiments are associated.

IV. Implementation of the Framework

The proposed framework is implemented as a client-server system named "Opinion Miner". In this system for opinion Mining and Sentiment Analysis, first of all comments of a user specified at a Facebook post are extracted. To do this, the user provides a URL of the post (status, picture or video) to this system and all comments by people are extracted by this system automatically to analyze sentiments and opinions.

User enters a URL of Facebook post. The URL firstly is verified that, Is it a Facebook URL? and If it is a URL of a status, picture or a video of Facebook then the system extract the Facebook Id of that content from the URL. It is worthy to mention that, as system is going to extract comments from a Facebook post, so the user has to login in Facebook to access Facebook contents.

On Facebook primarily there are three types of posts
1) Status
2) Picture
3) Video

Therefore, Facebook has constructed different types of URL structures to identify above categories few examples are given below.

https://www.facebook.com/Sohail.aka.Azizi/posts/**10151493851015848**

https://www.facebook.com/photo.php?fbid=**519234448124617**&set=a.277428618971869.60620.238358809545517&type=1&ref=nf

https://www.facebook.com/photo.php?fbid=**613105262047347**&set=at.101829533174925.4148.100000436370858.1498174194.1057787359&type=1&relevant_count=1&ref=nf

https://www.facebook.com/permalink.php?story_fbid=**447262618678275**&id=124433877627819

https://www.facebook.com/photo.php?v=**10102679448949689**&set=vb.20531316728&type=3

Overview of the application's data acquisition process is presented in Fig. 3.

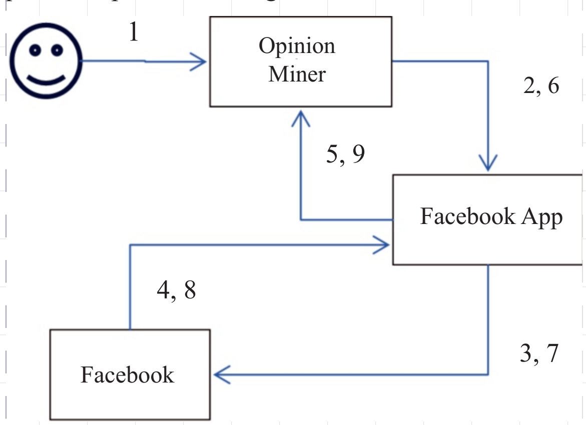

Fig. 3. Data Acquisition Process

Various steps depicted in the Fig. 3 are explained as follows:

1. The blue highlighted numbers in above URLs are the actual post ids of Facebook. Which then are extracted out to get all comments of the posts.
2. First of all it is checked whether the user is already login from Facebook? If not then the systems provides a window where he can login to Facebook in order to use this application.
3. The login user from Facebook is then checked by a Facebook App designed in this system.
4. On the successful login, Facebook provides an authorization key of that particular user to systems' Facebook App.
5. This Facebook App then provides that

authorization key to the system for further process for example getting comments.
6. At this step, this system uses Facebook post id (extracted in step 1) to get comments. So that, Id could be sent to the Facebook app.
7. Facebook App gives this post Id to Facebook in order to get all of comments related to that Id.
8. Facebook provides all the comments to Facebook App which were requested in step 7.
9. Facebook App provides all the comments to Opinion Miner.

At this stage, the Facebook App provides extracted comments to the system. Now Opinion Mining and Sentiment Analysis techniques are applied as described in the Section III.

As the process of fetching comments from Facebook and applying opinion mining and sentiment analysis algorithm on it is very time taking task therefore proposed framework divided this process into client and server programs. Each time server side of the implementation of the system fetches and analyzes100 comments then it shows cumulative sum to user/client side. These comments, their sentiments and opinions are displayed graphically on client site. Client server architecture and the overview of intercommunication protocol are depicted in the Fig. 4.

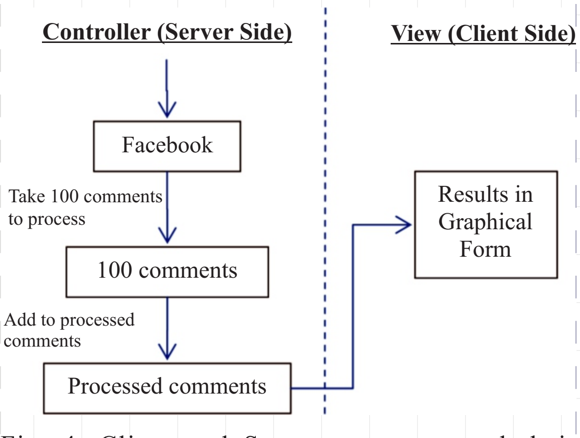

Fig. 4. Client and Server processes and their intercommunication

V. Experiment and Results

For the evaluation of the proposed system, human judgments are used. System is presented to public and they were asked to comment about the accuracy of this system. A set of randomly selected posts from Facebook and user comments on these post were collected. These posts with comments were given to a set of judges to gauge sentiment and opinions in these posts. These posts were classified in to three classes namely positive, negative, and neutral by the judges. Judges were briefed about these classes earlier on and they have provided their feedback accordingly. Randomly 100 post of each class (positive, negative, and neutral) were selected and presented to the system. The system fetched and analyzed posts with comments and accumulated sentiments and opinions depicted in those posts. After this a detailed comparison is performed between classification of human judges and the system and results are reported in follow paragraphs.

Table II presents results of above experiment. In this table the terms PC and AC stands for predicted class and actual classes respectively. Here PC means the class of sentiment of comments predicted by the system while AC means the class of sentiment of comments identified by the user which is considered as actual class.

In Table II details about confusion matrix or contingency table of the above experiment is represented. Through this confusion matrix several accuracy and performance measures of the proposed system could be easy observed like how much comments the system has classified truly as positive, negative and neutral, and how much these comments are wrongly classified as positive, negative and neutral etc.

TABLE II
MULTICLASS CONFUSION MATRIX OF THE SYSTEM'S PERFORMANCE

	Positive (PC)	**Negative (PC)**	**Neutral (PC)**
Positive (AC)	78	7	15
Negative (AC)	6	84	10
Neutral (AC)	21	13	66

First row entry in above table could be read as seventy eight (78) posts from positives post marked by human judges were classified as positive by the system while seven (7) and fifteen (15) of positives post marked by judges are classified negative and neutral by the system. Here it could also be observed from Table II that system has been facing a slight difficult in differentiating between positive and neutral sentiments and opinions, as fifteen (15) records which were positive were predicted as neutral and twenty one (21) neutral records were predicted as positive. It should be noted that system is not highly misclassifying between positive and negative classes which are in-fact opposite classes.

For aggregated analysis of this multiclass confusion matrix either of macro or micro averaging technique could be used [xxiii] as total number of records in sample are equally distributed among different classes. To calculate binary confusion matrix for above multiclass confusion matrix first we have construct binary confusion matrix for class namely positive, negative and neutral which are presented in Table III, Table IV and Table V respectively.

TABLE III
BINARY CONFUSION MATRIX FOR POSITIVE CLASS PREDICTION

	Positive (PC)	Not Positive (PC)
Positive (AC)	78	22
Not Positive (AC)	27	173

TABLE IV
BINARY CONFUSION MATRIX FOR NEGATIVE CLASS PREDICTION

	Negative (PC)	Not Negative (PC)
Negative (AC)	84	16
Negative (AC)	20	180

TABLE V
BINARY CONFUSION MATRIX FOR NEUTRAL CLASS PREDICTION

	Neutral (PC)	Not Neutral (PC)
Neutral (AC)	66	24
Not Neutral (AC)	25	175

Binary confusion matrix for the multiclass confusion matrix presented in Table II can be calculated as an accumulated binary confusion matrix using Table III, IV, and V presented as in Table VI.

TABLE VI
ACCUMULATED BINARY CONFUSION MATRIX FOR OVERALL PREDICTION OF VARIOUS CLASSES IN TABLE III, IV, AND V

	Neutral (PC)	Not Neutral (PC)
Neutral (AC)	228	62
Not Neutral (AC)	72	428

Now various measures for the proposed system's performance based on Table 6 could be calculated as True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) for the system are 228, 72, 62 and 428 respectively.

Accuracy of a binary classifier can be calculated as follows

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (1)$$

From Eq. 1 and using data from Table III, IV and V it could be observed that the system has accuracy of 83.66% on positive posts while 88.00% and 83.10% on negative and neutral posts. To calculate average accuracy (the average of per-class effectiveness of the classifier) Eq. 2 is used which resulted average accuracy 84.92%.

$$Average\ Accuracy = \frac{\sum_{i=1}^{l} \frac{TPi+TNi}{TPi+FNi+FPi+TNi}}{l} \quad (2)$$

In Eq. 2 TPi and others represent True Positive of ith class etc. while *l* represents total number of classes.

Average Error Rate (the average of per-class classification error) is calculated using Eq. 3 as follows which resulted into 15.08%.

$$Average\ Error\ Rate = \frac{\sum_{i=1}^{l} \frac{FPi+FNi}{TPi+FNi+FPi+TNi}}{l} \quad (3)$$

Precision which tells an average per-class agreement of the human judges with the system classification is 75.86% which is calculated using Eq. 4.

$$Precision = \frac{\sum_{i=1}^{l} \frac{TPi}{TPi+FPi}}{l} \quad (4)$$

Recall which tells an average per-class effectiveness of the system to identify judgment of human judges is calculated using Eq. 5 which is 78.44%.

$$Recall = \frac{\sum_{i=1}^{l} \frac{TPi}{TPi+FNi}}{l} \quad (5)$$

VI. CONCLUSION

An enormous increase in online user generated text, has recently motivated researchers to focus on design of new computational techniques which could meet different requirements of the sentiment analysis and mining of writer's opinion in the text [iii]–[v]. Approaches used in literature for sentiment analysis and opinion mining could be dived into three types namely, machine learning, Lexicon and hybrid [iii], [xix]. Machine learning based approaches mainly use supervised learning [xix], [xx] where a piece of text is compared with human developed list of sentiment bearing words. While Lexicon based techniques [xxi] are based on proper grammatical check on the text using various methods of Natural Language Processing. These techniques are mandatory for text where proper grammar has been used. Finally Hybrid techniques use combination of above mentioned and related techniques for sentiment analysis and opinion mining.

As the current study is focused on the sentiment analysis and opinion mining from the text of online social media namely Facebook and the text on Facebook carries formal as well as informal text expressions, hence the proposed framework is based on a hybrid technique. In this paper a novel sentiment analysis and opinion mining framework is proposed. This framework utilizes various techniques of computational linguistics to measure sentiment orientation of user's opinion around different entities. A rule base is designed for identification of sentiment orientation in the text and a list of named entities is populated from Wikipedia to recognize different Name Entities (NE). The proposed framework is used to perform sentiment analysis and opinion mining of users' posts and comments on social media through a Facebook App. Furthermore a user study is conducted to gauge performance of the proposed framework. The results of this study have shown that the framework is capable of finding opinions of the users and sentiments around those opinions with more than 85 percent accuracy when compared with actual human judges.

VII. FUTURE WORK

For future work a better sentiment lexicon could be designed to improve accuracy of the system. In particular as observed that the existing system muddled up positive and neutral sentiment, hence new sentiment lexicon can care about this. Also as current system extract only two types of entities, namely people and places. In future extensions it could be enhanced to cars, universities, drugs and many other types of entities which would be of great use. Moreover, as on social media people usually use slang and informal text, it would be an interesting challenge to understand informal expression so that a better sentiment analysis and opinion mining system could be developed.

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