Measuring the Influence and Intensity of Customer's Sentiments in Facebook and Twitter

Rashmi Sharma
Senior Assistant Professor - HR
Lal Bahadur Shastri Institute of Management, Plot No. 11/7, Sector-11, Dwarka
New Delhi-110075 Email: rashmi@lbsim.ac.in

Hemlata Sharma
Senior Assistant Professor – IT
Lal Bahadur Shastri Institute of Management, Plot No. 11/7, Sector-11, Dwarka
New Delhi-110075
Email: hemlatasharma@lbsim.ac.in

Pallavi Sharma
Senior Assistant Professor - IT
Lal Bahadur Shastri Institute of Management, Plot No. 11/7, Sector-11, Dwarka
New Delhi-110075
Email: pallavi@lbsim.ac.in

***Abstract*— Organisations these days are actively using social media platforms to engage with potential and existing customers and monitor what they say about the organisation's product or service. The most important area within social media monitoring lies in how to gain insight for sentiment analysis. Sentiment analysis helps in effective evaluation of customer's sentiments in real time and takes on a special meaning in the context of online social networks like Twitter and Facebook, which collectively represent the largest online forum available for public opinion. Sentiment Analysis is not about retrieving and analyzing the analytics purely on the basis of positive, negative or neutral sentiment. It is imperative to assess the influencers of the sentiments in terms of Retweet and Share option used by them on Twitter and Facebook platform respectively. Measuring the intensity is other important aspect of sentiment analysis process. What kind of nouns, adjectives, verbs and adverbs are used in the opinion across the Twitter and Facebook platform matters as well since it exhibits the intensity of the underlying emotion in the text written. This study was conducted to propose a framework to identify and analyse the positive and negative sentiments present in Twitter and Facebook platforms and an algorithm was prepared to measure the intensity and influence of the positive, negative sentiment in particular using the document and sentence level analysis technique.**

Keywords- Sentiment Analysis, Influence, Intensity, Social Media monitoring, sentence level analysis, document level analysis

I. INTRODUCTION

Sentiment analysis is being considered as the most contemporary area of research in recent times. With the advent of social media platforms like Twitter and Facebook, people all across the world are not only using these forums for social networking but also to share opinions and reviews about a certain product or service. People interact with family, friends and even strangers to discuss just about anything; from brands, movies and celebrities to social and political activities. However, this user generated content on social sites are presenting unique challenges in harnessing, analyzing and interpreting textual content since data are dispersed, disorganized and fragmented [1]. Through sentiment analysis, marketers collect data on customer's sentiments to gain insights about the customer's feelings and perception. Sentiment analysis gives an opportunity to know the feelings and attitude of customer in real time despite the challenges of data structure and volume. Marketers have recognized the profound influence of social communities on consumer behavior [2], [3]. The decision making process of people is affected by the opinion and reviews of others. Thus, we may say that the recent explosion in user generated content is presenting enormous challenges for marketers [4] as one has to identify the subtleties in each message and prioritizing what is the most important sentiment (intensity) and what kind of impact it would have on other's mind (influence).

I.(a) INFLUENCE: Since the chatter on social media is enormous, the marketers have to pick the sentiments that can grossly damage or build the organisation's reputation. Twitter allows one to write messages on any topic within a 140 characters limit and higher percentage of updates are neutral on Twitter than on Facebook. However, for the positive or negative sentiment, the Twitter users can be the most influential people in terms of RT which stands for `retweet' (that is the action of forwarding another user's tweet to all other followers that one has). In Twitter, users can follow any other user without permission, i.e. the relationship of following requires no reciprocation. Thus, if someone has made a negative mention about an organisation's product/ service, marketers have to understand how far each tweet travelled and how many people were influenced by the content. Recently, there have been several investigations into the role of Twitter in social media. Some researchers focused on understanding microblogging usage and community structures [5], [6], [7]. Other researchers [8] considered three measures of influence viz. indegree (the

DOI: 10.5176/2345-7872_1.2.19

number of followers), retweets, and mentions. They found that indegree represents a user's popularity, but does not necessarily correspond to a user's influence; therefore, retweets and mentions should be considered as other important Measures of influence. In this paper the focus is only on retweets in Twitter platform.

Facebook is an SNS used primarily to connect, interact and stay in touch with contacts that the user knows personally, such as friends, family and colleagues [9]. Facebook is one of the most popular Social Networking Sites [10]. As per some researchers, [11], [12], of the seven motives of using Facebook, one of the motives is for learning purpose. In other words, people use Facebook to communicate with one another to share information and opinion. In Facebook the option Share is used by the users to pass on with others crucial content which has in form or the other deeply impacted the mind of the user and subsequently the user wants others to know about it. The content may have a positive, neutral or a negative sentiment but it gets magnified when it is shared. In other words, the Share option in Facebook has an influence on the sentiments of users with whom the content was shared with.

I(b) INTENSITY: As far as sentiment analysis is concerned, part of a successful prioritization process is going to be identifying the intensity of each mention. "The memory size of Mobile A is horrible" is stronger in intensity than "I wish Mobile A had higher memory size". Only 4 kinds of words can express the sentiments. They are: Nouns, Adjectives, Adverbs and Verbs. In this paper, noun is being used as an object and feature. For example in the statement: "The screen of mobile A is good"; here `mobile' and `screen' are both nouns but the word `mobile' is an object and `screen' is a feature. Therefore, to analyse the sentiments, in this paper we would focus on adjectives, verbs and adverbs. As stated earlier, sentiment is of three types i.e. positive, negative and neutral but users pay attention to only positive and negative sentiments. Also, the term presence and term position are considered vital in sentiment classification.

Some researchers [13] found that term presence is most important in information retrieval. The presence of a single string sentiment bearing words can reverse the polarity of the entire sentence. For example "The mobile phone A is good, has unique features, good display but the battery life is poor". In this case the presence of terms (adjectives) like 'good', `unique' are marred by the position of the term `poor' in the end of the sentence. In other words, although the sentence has positive words throughout, the presence of a negative sentiment at the end sentence plays the deciding role in determining the sentiment.

Adjectives have been used most frequently as features amongst all parts of speech. A strong correlation between adjectives and subjectivity has been found. Although all the parts of speech are important, but people most commonly used adjectives to depict most of the sentiments and a high accuracy have been reported by all the works concentrating on only adjectives for feature generation. The researchers [13] achieved an accuracy of around 82.8% in review domains using only adjectives. Some of the adjectives for sentiment identification may be as follows:

Positive Adjectives: good, amazing, dazzling, brilliant, phenomenal, thrilling, unique, fantastic, excellent

Negative: Horrible, pathetic, bad, poor, suck, terrible, awful,slow, weak

Most of the adverbs have no prior polarity. But when they occur with sentiment bearing adjectives, they can play a major role in determining the sentiment of a sentence. It has been shown how the adverbs alter the sentiment value of the adjective that they are used with [14]. Adverbs of degree, on the basis of the extent to which they modify this sentiment value, can be classified as:

- Adverbs of affirmation: certainly, totally
- Adverbs of doubt: maybe, probably
- Strongly intensifying adverbs: exceedingly, immensely, extremely
- Weakly intensifying adverbs: barely, slightly
- Negation and minimizers: never

Sentiment analysis can be a powerful tool only when marketers would identify the deeper meaning behind what is being said and the reachability of the sentiment in a web. 2.0 platform that is known for viral dissemination of information.

II. OBJECTIVES OF THE STUDY

The present study seeks to achieve the following objectives:

1. Develop a framework to identify and analyse the positive and negative sentiments present in Twitter and Facebook platforms.
2. Design an algorithm that would measure the influence and intensity of the sentiments using the document and sentence level approach of sentiment analysis.

III LITERATURE REVIEW

More than 75% of the social media users confirm that customer's reviews have a significant influence on their purchase and they are willing to pay more for a product with better customer review [15]. In other words, customers trust the opinion of someone on social media more than the traditional promotional messages. Thus, customer's sentiments are to be analysed for the influence and intensity because it shapes the purchasing behavior of people who follow them on Twitter and are on the friend's list in Facebook. A study done in April 2010 by ROI Research, commissioned by Performics, revealed that at least once a week, 33% of active Twitter users share opinions about companies or products while 32% make recommendations and 30% ask for them. In 2008, Pew Internet and American Life Project Report that was focused on online shopping behavior identified that more than 80% of US internet users have previously done online research about a product or service. More than 75% of online-hooked customers confirm that reviews have a significant influence on their purchase and they are willing to pay more for a product with better customer reviews. In addition to that, 1/3 rd of users post an online review or rating regarding a product or service, thus, becoming an influencer themselves. [16]

A detailed and comprehensive review on effective computing and computer technology for emotion and expression recognition was presented by some researchers [17]. Computing technology brings about measurability and objectivity to the sentiments generated on the social media platforms. Extracting emotions from natural language processing and algorithms is becoming popular amongst researchers and practitioners.

It is common to classify sentences into two principal classes with regard to subjectivity: objective sentences that contain factual information and subjective sentences that contain explicit opinions, beliefs and views about specific entities. As per the researcher [18], there are five specific problems within the field of sentiment analysis:

- Document level sentiment analysis
- Sentence level sentiment analysis
- Aspect based sentiment analysis
- Comparative sentiment analysis
- Sentiment Lexicon acquisition

In this paper we would focus only on document level and sentence level sentiment analysis.

Document-Level sentiment analysis**:** This approach assumes that the document contains an opinion on one main object expressed by the author of the document. There are two main approaches to document level sentiment analysis: supervised learning and unsupervised learning. The supervised approach assumes that there is a finite set of classes into which the document should be classified and training data is available for each class. The simplest case is when there are two classes: positive and negative. Accuracy of 80% is achieved when the document is presented as text with simple text. Unsupervised approaches to document-level sentiment analysis are based on determining the semantic orientation (SO) of specific phrases within the document. If the average SO of these phrases is above some predefined threshold the document is classified as positive and otherwise it is deemed negative.

Sentence-Level Sentiment Analysis: A single document may contain multiple opinions even about the same entities. In order to have an in-depth view of the different opinions expressed in the document about the entities one has to move to the sentence level. It's assumed that we know the identity of the entity discussed in the sentence. It's also assumed there is a single opinion in each sentence. This assumption can be relaxed by splitting the sentence into phrases where each phrase contains just one opinion. Before analyzing the polarity of the sentences one must determine if the sentences are subjective or objective. Only subjective sentences will then be further analyzed. (Some approaches also analyze objective sentences, which are more difficult). The approach works when neighbouring sentences also have the same subjectivity classification. It is advisable to handle different types of sentences by using different strategies.

A method was proposed to handle sentiment analysis for opinion mining of Cantonese which belongs to the ancient Chinese language and a method for feature orientation summarization [19]. Author used Hidden Markov model (HMM) which is a sequential probability model, describing a process that an unobservable random state sequence generated by a hidden markov chain generates an observation random sequence [20] to conduct word segmentation, and then building opinion orientation dictionary for Cantonese. In developing this paper the author faced some critical challenges in terms of building up the POS (Parts-of-speech) system and the sentiment word dictionary for Cantonese. Thus, they categorized there work into two parts. First, they solved these above cited problems and then they applied opinion mining techniques to complete the other subtasks.

A system called opinion miner was designed which automatically combined supervised learning that is capable of extracting, classifying and learning tweets, with opinion expressions of a person [21]. The researchers used domain-specific training data to build a generic classification model from social media data to help and improve the performance of the system. The author then tested the effectiveness of the whole system by demonstrating experimental results on twitter. System architecture was introduced that extracted tweets with opinion from Twitter, and then performed some pre-processing steps. Subsequently, tweets with opinion in them were extracted and classified as per their categories. Training data of different categories was used to build classifiers. Researchers focused on microblogging data like Twitter, on which users post real time reactions and opinions about `everything'. They used it for majorly `Camera', `Mobile' and `Movie'. The major problem they faced was that, the messages on microblog were short, filled with colloquial terms and grammatically incorrect. In this context the researchers decided to design opinion miner and suggested approach that classifies opinion texts or sentences as positive, negative or neutral [22-27].

A tree kernels structure was proposed for mining opinion of online reviews [28]. The researchers concluded that performance of tree kernels structure is improved significantly for extraction and classification of sentiment expression. The author dealt with this problem as a classification problem and solved it by using machine learning algorithms, first decomposed the tree (sentiment expression) into FST(Featured segment tree), GFST (Generaliazed Feature sentiment tree), $GFST^m$ (boundary marked GFST)and $GFST^p$ (GFST with polarity)for the target feature node.The author then combined all these kernels with traditional kernel to compute the similarity between two vectors. To determine the polarity point wise, mutual information method is used as the sentiment polarity of a word usually depends on the target features. Results of the study showed that the performance of proposed tree kernels is best out of linear combination of tree kernels and polynomial kernels.

A conditional random field (CRFs) was proposed to tackle discriminative learning model and for product feature extraction [29]. The researchers incorporated part of speech features and sentence structure features into CRF's Learning process and product feature categorization .The author calculated the similarities between product feature expressions of two measures of similarities and an algorithm was proposed by combining these two measures to clarify the collection of feature expressions into different semantic groups. The effectiveness of which was proved by empirical studies and efficiency of their approach was compared with other counterpart methods.

Some researchers proposed a technique to mine product features by using a SentiWordNet based algorithm [30], [31] which employed data mining and natural language processing methods and categorized entire task into three steps. First, sentiment sentences were identified from each review by applying POS tagging. Four kinds of words were considered to express the sentiments –noun,adjective, verb and adverb .Sentiment Score of each sentence was acquired from SentiWordNet and the positivity and negativity of each word was finally calculated.

Second the product features were identified about which the user had commented on and in the end features were pruned to remove unwanted and redundant features. The author highlighted that the proposed technique could get 92% in precision and 90 % in recall.

A statistical approach for identifying features of opinion by capturing the disparities in domain relevance was also proposed by some researchers [32]. The researchers first extracted candidate feature and then distributed the structure into two corpus i.e. Domain-specific and domain–independent. Researchers calculated the intrinsic and extrinsic domain relevance scores Intrinsic Domain Relevance (IDR) and Extrinsic Domain Relevance (EDR) respectively on each of the corpus. Candidate features which were less generic and more domain specific were confirmed as opinion features Experimental results demonstrated that the proposed intrinsic and extrinsic domain relevance (IEDR) led to noticeable improvement over with IDR or EDR and also outperformed four mainstream methods namely, LDA(latent Dirichlet allocation),ARM(Association Rule Mning),MRC(Mutual reinforcement clustering) and DP(Dependency Parsing) in terms of feature extraction performance as well as feature based opinion mining . Author also evaluated the impact of corpus size and topic selection on feature extraction performance and finally concluded that using a domain-independent corpus of same size but of different topics will give good opinion feature extraction results.

Through the literature review we may elucidate that measuring the intensity of a sentiment and assessing it's influence on the opinion of users/readers of Twitter and Facebook had escaped the minds of the researchers and thus, the present study was conducted.

IV DISCUSSION

i. PROBLEM STATEMENT

User on Facebook & Twitter typically gives review of the product of items they have used. Their review provides overall opinion about product. There is a large amount of data records related to products on the web, which can be of use to both the marketer and the user. Each review can have an influence on the mind of the reader, and the intensity with which it affects the opinion of the user. In this paper, we suggest a framework to measure the intensity and influence of each review. We have also proposed an algorithm for implementing the suggested framework.
The problem can be modeled by a triplet (*U*,*P*,*R*).
U is the user identifier set {u1,u2,u3…..ui}
P is the product category identifier set
{p1,p2,p3…pj}.. R is the review set {r1,r2,r3….rk}

The goal of our algorithm is to measure the intensity and influence of each review.
However, a review usually contains user's sentiment about different aspects of each product/service category. For a given number of product/service category (P), we use --R to denote user Ui review.

ii. FRAMEWORK

We propose a framework to utilize the multiple aspects of sentiments in the review. This framework mainly consist of two parts namely 1) Sentiment extraction and classification & classification and 2) Intensity and influence calculation.

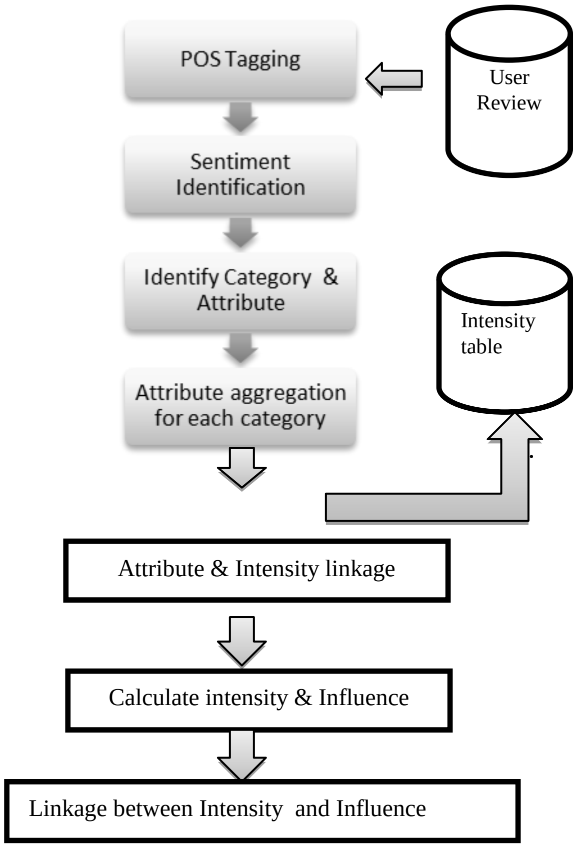

Figure 1: Framework to Measure Intensity & Influence of Sentiments

iii. THE PROPOSED TECHNIQUE

An overview of our framework is given in figure 1. The system performs the intensity and influence calculation at both document as well as sentence level in two main steps: Sentiment Identification using SentiWord-Net based algorithm (Hu, Gong et.al, 2010) and Intensity and Influence Calculation.

The input to the system is all the reviews of the different categories of products in the database. The output is the intensity and influence value.

We downloaded reviews from Twitter and Facebook and put them in a review database. Firstly we identified the product category that a lot of people have expressed their positive or negative opinions on, and then extracted the different part of speech from them, so as to identify the feature about which the user has given his/her review. Finally we linked each attribute to its intensity using a predefined intensity table and calculated the value of intensity and influence. The function of each framework is explained below:

A) *POS Tagging* – POS tagging_refers to part of speech tagging from natural language processing. From the review, we extracted individual sentences and tagged each word with its part of speech to identify the product category and feature about which the user is expressing his/her sentiment.

Liu et al.(2009) defined sentiment as a quintuple- *"<oj,fjk,soijkl,hi,tl>,where oj is a target object,fjk is afeature of the object oj,soijkl is the sentiment value of the opinion of the opinion holder hi on feature fjk of object oj at time tl, soijkl is +ve,-ve,or neutral, or a more granular rating ,hi is an opinion holder, ti is the time when the opinion is expressed."*

POS tagging helped us in identifying various aspects of a sentence which further helped in identifying phrases in a text that bore some sentiment.

Consider the following example-

The steering of the car is unpredictable,
In this example object is `car', feature is `steering' and the adjective is `unpredictable'.

B) *Sentiment Identification* –our main concern was about identifying what user likes or dislikes. So we had to extract those sentences where user has expressed their sentiments. Only four kinds of words can express the sentiment, they are noun, adjective, adverbs and verbs. Since noun is being used as a category feature here; our focus is on adjectives, adverbs and verbs as sentiment words. Sentiment includes three types: positive, negative and neutral. Neutrality describes a fact and users, usually pay much attention to the positivity and negativity.

For instance let us look at the following sentences:
"The performance of this Tablet is extremely good."
"I bought this Tablet yesterday"

In the first sentence, the feature `performance' is considered, but in the second no feature exists so we can discard the second one.

The sentiment identification was done using SentiWordNet (Hu, Gong et.al, 2010), which is a lexical resource for sentiment mining.

C) Identify category & attribute
In this step we identified the product category and attributes about which the user had spoken.
For instance in the sentence:
`The performance of Tablet is excellent'
In this the category is `Tablet' and the attribute is `performance'.

D) <u>Attribute aggregation</u>- In our proposed algorithm after POS we identified two sets P for identifying product/ service category and T for attributes represented as token. We put the object represented by the set O in set P and attributes (adverb, adjective, and verb) represented as token in set T. Tokens belonging to the same object were kept in the same set.

E) <u>Attribute and Intensity Linkage</u> –
We captured the intensity of each token in set T with the help of a pre-defined intensity table.

F) <u>Calculate Intensity & Influence</u>-
Finally the intensity was obtained by using Algorithm 1 and Influence was obtained by using Algorithm 2 as given below:

Algorithm 1: algorithm for calculating Intensity

```
Require: The clusters of reviews /user reviews[R]
         The set of Product P_i, where i is the no of
         Products
         The Set of attribute defined as token in set
         T.
Ensure:  //Check weather Document level or
         Sentence level
  For each Review [R]
     initialize i  with string length
   // Find Intensity of each Sentence
     For( j=0: j< i; j++)
        For each sentence Si belongs to [1,D]
         do,
        //D implies Entire Document
           Initialize Ps=0, Ns=0
  //Ps for positive Intensity measure, Ns Negative
  Intensity measure.
            For each w ϵ {S1} do  // w refers to word
              POS Tagging
             //Identify Object(noun) and attribute
              (adverb, adjective etc.).
              Initialize empty set T and  O
               //Put object in set 'O' and attributes
                in  set T.
              //initialize set P with set O
               For each object o
                   ϵ O and Token t ϵ T do
                 If o appears in Si then
                   P = P U {o}
                 Endif
                If t appears in Si then
                 If t ϵ {".",".....","-",",",";","!","?"}
    Then break
   Else
      T=T U {t}
   Endif
  Endfor
  // Rate intensity for product P
      For each p ϵ P do
          For all t ϵ T do
            initialize t with its intensity
        If the sentiment polarity of t is
               positive then
             Ps =Ps+1
         Else
              Ns=Ns+1
         Endif
        EndFor
     Endfor
    EndFor
 EndFor
 If Ps-Ns>0 positive intensity is high
  Else
 Negative Intensity is high
```

Algorithm 2 : algorithm for calculating Influence

```
Require:  Set Ss for counting no of share.
          Set Tw for counting number of tweet
Ensure:
  For each Product p ϵ P
    For each S, D ϵ R do
      Initialize Ss=0,tw=0,
      If user Click = = share
        Ss= Ss+1
       Endif
      If user Click= = retweet
       Tw= Tw+1
       Endif
      Endfor
    Endfor
  //threshold being any predefined value
  If  Ss and Tw > threshold influence is high
   Else
  Influence is low.
```

---

iv EXPERIMENTS

In this section, we evaluated the whole system and presented result for Facebook & Twitter. The main task was to classify tweets and Facebook post to positive and negative versus neutral. Presented below are the results of intensity and influence of the reviews cited as data in this case.

In our experiment we used sets of around 800 reviews for 4 products: Digital camera, DVD Player, Mobile phone, Tablet. Out of the 800 reviews, 58 reviews were neutral both on Twitter and Facebook. The system used SentiWord-Net synonyms/antonyms in order to find the actual sentiment words. Finally a predefined intensity table was used to find the intensity of each word. Testing data tables is presented below:

Testing Data 1

Product Name	No of Reviews	Positive	Negative	Neutral
Mobile ph	182	11	140	31
DVD Player	210	116	35	59
Digital camera	118	62	29	36
Tablet	232	40	66	126

Testing Data 2

Product Name	No of Retweets	No of share
Mobile Phone	2	4
DVD Player	1	2
Digital Camera	3	-
Tablet	0	1

v RESULT-

The result of each part of the framework proposed is shown below:

1) Calculating Intensity- Results for measuring the intensity is mentioned below in table 1. In this paper we have treated sentences with positive and negative polarity. We have not considered the neutral sentiment in this case.

Product Name	Intensity
Mobile Phone	Low
DVD Player	High
Digital camera	High
Tablet	Low

Table 1: Calculating Intensity

Similarly there are many types of sentences like `I want mobile B' or `I want my brother's tablet'. In these examples we may feel there is positive sentiment, but the intensity is not so high of the opinion. Thus, we had focused only on positive and negative sentiments and the accuracy came to be 82%. We observed that the weight of positive data was higher than negative data, so the result was positive

2) Influence Calculation- We considered the value given in testing data table 2 and got the following result :

Product Name	Influence
Mobile Phone	High
DVD Player	Low
Digital camera	Low
Tablet	Low

Table 2: Measuring Influence

Since we had taken a threshold value for calculating influence, so we can say the accuracy in this case is 70%.

Comparison – Finally we combined the result of both the tables to show the final result as given in Table 3.

Product Name	Intensity	Influence
Mobile Phone	High	Low
DVD Player	High	Low
Digital Camera	Low	High
Tablet	Low	low

Table 3: Linkage between Intensity and Influence

We found that there is no direct relationship between the intensity and influence of the sentiment, even if the intensity is high, influence can be low as there are many users who may not retweet or share the positive or negative sentiment.

IV CONCLUSION

We designed a framework through which the intensity and influence of the sentiment could be measured for opinions posted and shared on Twitter and Facebook platform. Our algorithm tested well in measuring intensity and influence of sentiments in Twitter and Facebook. In this paper, we had only considered textual reviews and had done our analysis on the basis of those reviews. In our future work we plan to further improve and refine our techniques in order to enhance the accuracy of the system. The following may be treated for future research in the area if intensity and influence measurement with respect to sentiment analysis:

(1) Data depicting emotions through emoticons and numerical rating data can be considered for determining the intensity of sentiments.

(2) Features like tagging and like option of Facebook can be incorporated to determine the influence.

All in all, we may say that influence and intensity of the sentiments should be analysed by the marketers. The proposed framework and algorithm would help to understand the opinions and assess the collective trend and mind of the market so that remedial strategies and brand campaigns can be adopted by the organisations in controlling the negative sentiment or propagating the positive sentiment.

REFERENCES

1. Kaplan, Andreas, M., and Haenlein, Michael. (2010). “Users of the World, Unite! The Challenges and Opportunities of Social Media.” *Business Horizons*, 53 (1): 59-68.
2. Gruen, Thomas W., Osmonbekov, Talai, and Czaplewski, Andrew J. (2006). “EWOM: The Impact of Customer-To-Customer Online Know-How Exchange on Customer Value and Loyalty.” *Journal of Business Research*, 59 (4): 449-456.
3. Park, Do-Hyung, Lee, Jumin, and Han, Ingoo. (2007). “The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement.” *International Journal of Electronic Commerce*, 11 (4): 125-148.
4. Stanton, Jeffrey, M., and Rogelberg, Steven, G. (2001). “Using Internet/Intranet Web Pages to Collect Organizational Research Data.” *Organizational Research Methods*, 4 (3): 200-217.
5. Honeycutt, C., & Herring, S. C. (2009). “Beyond microblogging: Conversation and collaboration via Twitter.” In Proceedings of the 42nd Hawaii InternationalConference on System Sciences (HICSS-42) Los Alamitos, CA: IEEE Press.
6. Huberman, B. A., Romero, D. M., & Wu, F. (2008). “Social networks that matter: Twitter under the microscope.” Retrieved from http://ssrn.com/abstract=131345

7. Java, A., Song, X., Finin, T., & Tseng, B. (2007). “Why we twitter: Understanding microblogging usage and communities.” Paper presented at the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis, San Jose, California.
8. Cha, M., Haddadi, H., Benevenuto, F. L., & Gummadi, K. P. (2010). “Measuring user influence in twitter: The million follower fallacy.” Paper presented at the 4th International AAAI Conference on Weblogs and Social Media (ICWSM), Washington DC, USA
9. Ellison, N. B., Steinfield, C., & Lampe, C. (2007). “The Benefits of Facebook "Friends:" Social Capital and College Students' Use of Online Social Network Sites.” Journal of Computer Mediated Communication , 1143-1168.
10. Lampe, C., Ellison, B., & Stein field, C. (2008). “Changes in Use and Perception of Facebook.” Proceedings of the 2008 ACM conference on Computer supported cooperative work (pp. 721-730). New York: ACM
11. Hew, K. F. (2011). “Students’ and teachers’ use of Facebook.” Computers in Human Behavior , 27, 662–676.
12. Roblyer, M. D., McDaniel, M., Webb, M., Herman, J., & Witty, J. V. (2010). “Findings on Facebook in higher education: A comparison of college faculty and student uses and perceptions of social networking sites.” Internet and Higher Education, 13(2010), 134–140.
13. Pang, B., Lee, L. and Vaithyanathan, S. (2002). “Thumbs up? sentiment classification using machine learning techniques.” Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10, Philadelphia, PA, USA
14. Balamurali A.R., Aditya Joshi, Pushpak Bhattacharyya. (2011). “Harnessing WordNet Senses for Supervised Sentiment Classification.” In Proceedings of EMNLP, Edinburgh, 2011
15. Kincl, Tomáš; Novák, Michal; Přibil, Jiří. “Getting Inside the Minds of the Customers: Automated Sentiment Analysis.” Proceedings of the European Conference on Management, Leadership & Governance. 2013, p122-128. 7p., Database: Business Source Complete
16. Huberman, B. A., Romero, D. M., & Wu, F. (2008). “Social networks that matter: Twitter under the microscope.” Retrieved from http://ssrn.com/abstract=131345
17. Pang, B. and Lee, L. (2008). “Opinion mining and sentiment analysis.” *Foundations and trends in information retrieval*, Vol. 2, No. 1-2, pp 1-135.
18. Ronen Feldman. (2013). “Techniques and Applications For Sentiment Analysis.” *Communication of the ACM* Vol. 56, No. 4
19. J. Chen,Y. Liu,G. Zhang,Y. Cai,T. Wang, H.Min. ,“Sentiment Analysis for Cantonese Opinion Mining”, Proceedings of fourth International Conference on Emerging Intelligent Data and Web Technologies.IEEE,2013.
20. H. Minqing, L.Bing. ,“Mining and summarizing customer reviews”,Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2004: 168-177.
21. Po. Liang, Bi.Dai,” Opinion Mining on Social Media Data”, proceedings of fortheenth International Conference on Mobile Data Management,IEEE,2013.
22. A-M. Popescu and O. Etzioni. *“*Extracting Product Features and Opinions from Reviews”. EMNLP-05, 2005
23. Kunpeng Zhang, Yu Cheng, Yusheng Xie, Daniel Honbo, Ankit Agrawal, Diana Palsetia , Kathy Lee , Wei-keng Liao , Alok Choudhary,. *“*SES: Sentiment Elicitation System for Social Media Data.” Proceedings of the 2011 IEEE 11th International Conference on Data Mining Workshops, p.129-136, December 11-11, 2011.
24. Apoorv Agarwal, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca Passonneau. 2011. *“*Sentiment analysis of twitter data.” In Proceedings of the Workshop on Languages in Social Media, pages 30–38. Association for Computational Linguistics.
25. Alec Go, *Richa Bhayani* ,*Lei* Huang,.: “Twitter sentiment classification using distant supervision.*”* In: CS224N Project Report, Stanford (2009)
26. X. Ding, B. Liu, and P. S. Yu, “A holistic lexicon-based approach to opinion mining,” Proceedings of the Conference on Web Search and Web Data Mining (WSDM), 2008.
27. Alexander Pak and Patrick Paroubek. 2010. *“* Twitter as a corpus for sentiment analysis and opinion mining.” Proceedings of LREC.

28. P.Jiang,C.Zhang,H.Fu,Z.Niu,Q.Yang, “An approach on tree kernels for opinion mining of online product reviews”, International Conference on Data mining,IEEE,2010.
29. S. Huang,X. Liu,X.Peng,Z.Niu, “Fine-grained Product Features extraction and categorization in reviews opinion mining”, Proceedings of 12th International Conference on Data mining workshops,IEEE,2012
30. W.Hu, Z.Gong, J.Guo,“Mining product features from online reviews”, International Conference on E-Business Engineering ,IEEE,2010.
31. A.Esuli and O.Etzioni ,“Extracting product features and opinions from reviews”, Proceeding of Human Language Technology Conference and Conference on Empirical Methods in Natural Language,ACL,Vancouver,October2005,pp.339-346.
32. Z. Hai, K. Chang, J. Kim, C. C. Yang ,“Identifying features in opinion mining via Intrinsic and Extrinsic Domain Relevance”, Transactions on knowledge and data engineering ,IEEE March 2014,Vol.4,No.3 pp.623-634.

Disclaimer: The data used for testing in this paper is hypothetical by nature. The names of the products and services have been changed to maintain confidentiality. The algorithm and framework proposed in the paper are intended solely for the use of the authors. Disclosing, copying, distributing or taking any action pertaining to the content cited in the paper is strictly prohibited. No researcher is authorized to adopt and apply the technique proposed in the paper to measure influence and intensity of opinion available on social media platforms without written permission from the authors.

AUTHORS’ PROFILE

Rashmi Sharma is Senior Assistant Professor-HR at Lal Bahadur Shastri Institute of Management, Delhi, India. She is Ph.D, M.Phil in Management, MBA and M.A. in English. Dr. Sharma has published several research papers in national and international journals. Her research interests include social media monitoring and sentiment analysis. She is the Editor of LBS Journal of Management & Research and registered co-guide for Ph.D programme of Banasthali Vidyapith. As an avid creative writer, she has to her credit several articles published in leading Indian newspapers and American e-magazines.
She organises, and is a key resource person for MDPs organised for middle and senior level managers of India’s leading Public Sector Undertakings, Engineers India Limited, NTPC and BHEL. She is also an invited speaker for an MDP organised (for middle and senior level officers of Lok Sabha and Rajya Sabha) every year by Bureau of Parliamentary Studies and Training. Dr. Sharma also delivers invited sessions in reputed institutes in India like Lady Irwin College(Delhi University), Banasthali Vidaypith,

Bhagat Phool Singh Mahila Vishwavidyalaya(a State University of Haryana), to name a few. She can be reached at rashmi_sharma.hr@rediffmail.com or rashmi@lbsim.ac.in.

Hemlata Sharma is Senior Assistant Professor-IT at Lal Bahadur Shastri Institute of Management, Delhi, India. She is currently pursuing M,Tech in CSE from Guru Gobind Singh Inderprastha University, New Delhi. She holds the MCA degree from Bangalore University, Karnataka. Her research interests include Natural language Processing, Algorithms and Data Mining. She can be reached at hemlatavashist@gmail.com or hemlatasharma@lbsim.ac.in.

Pallavi Sharma Received the MTech and MSc degrees in Computer Science from Banasthali Vidyapith, Jaipur (Raj), India.
She is currently working as Senior Assistant Professor at Lal Bahadur Shastri Institute of Management, Delhi, India. Her Current research interest includes Wirelesss Sensor Networks, Data Mining, Natural Language Processing and Digital Image Processing. She can be reached at: pallavisharma13@gmail.com, pallavi@lbsim.ac.in.