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OPINE_NEG: AN APPROACH TO DETECTING NEGATIONS AND INTENSIFIERS USING SOCIAL MEDIA DATA

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Abstract: With the abundance of online information available today, there are numerous opportunities and challenges that arise for both consumers and internet users alike. Managing customer satisfaction is a critical performance indicator for running a successful business. Opinion Mining, also called as sentiment analysis, is the method of digitally assessing public feelings, emotions, opinions, and services. This text mining technique and natural language processing are used to automatically extract, classify, and summarize sentiments and feelings expressed in online text. This study focuses on subjective terms in the user opinions collected from microblogging sites and analyses the semantic orientation of reviews to identify and classify negations, intensifiers, slang words, and emoticons. This study proposes an improved lexicon-based dictionary approach using a rule-based classification scheme to enhance the accuracy of opinion mining on Big Data. To test the efficiency of the research work, user reviews in four domains - mobile, health, electronic, and vehicle - were analysed using Twitter datasets.

Keywords: Opinion Mining, Microblog data, Negations, Intensifiers, Big Data.

I. INTRODUCTION

Opinion Mining, also called as Sentiment Analysis (SA), is a technique used in Natural Language Processing and text mining to automatically extract, classify, and summarize the sentiments, emotions, opinions, and attitudes expressed in online text. It involves analyzing data from various sources, such as social media platforms, blogs, and customer reviews, to determine the public perception of a particular product, service, brand, or topic. The primary goal of Opinion Mining is to classify and categorize the sentiment uttered in a piece of text [5]. This information can be used by businesses, organizations, and individuals to gain insights into customer satisfaction, market trends, and public opinions. Opinion Mining is a challenging task as it requires a deep understanding of the nuances of human language, including the use of sarcasm, irony, and other forms of figurative language [1]. Recognizing the polarity of reviews is a crucial component in opinion mining systems. Subjectivity identification is particularly important as subjective sentences express user opinions, whereas objective sentences convey facts without opinions. This subjectivity classification can be accomplished at three levels: Document level, Sentence Level, and Aspect level [2]. This research paper focuses on sentence level sentiment classification by considering slang terms, negations and intensifiers. Furthermore, this study proposes a algorithm named opine_neg to handle all the terms and classifies into positive, negative and neutral based on the term's weightage allocated by the SWN Lexicon [5].

II. RELATED RESEARCH WORKS

In a study by Wareesa Sharif et al., [6] the authors addressed the issue of consumer reviews containing positive language but conveying negative sentiments. While there are various approaches for handling negations in opinion mining systems, the authors found them to be inefficient and inadequate for accurately calculating negation sentiment. To address this, they proposed a modified negation approach that identifies and calculates sentiment based on dependencies between negation words. The approach goes beyond the use of typical negation words (never, not, n't,no). The researchers also examined how negation words affected the semantic nature of positive reviews that were, in reality, negative. The proposed method yielded better results for review classification in terms of accuracy with negation words. However, a limitation of the study was its failure to handle intensifiers. The authors focused solely on negations and did not account for the influence of intensifiers on opinion mining.

Bhaskar J. et al. [7] attempted to enhance sentiment classification by modifying the sentiment values derived from the SentiWordNet Lexicon. They projected a new technique for improving opinion classification of reviews from the product sites by accounting for intensifiers and objective words. Natural Language Processing, SentiWordNet lexical resource,

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and Support Vector Machines were used in their analysis. The researchers successfully handled negation and intensifiers, modified objective words, and calculated the semantic nature of the sentences. Some objective words were reassigned as positive or negative. The authors evaluated the sentiment classification with digital camera product reviews collected from Amazon and EBay. The experimental analysis revealed that the devised method improved the effectiveness of sentiment assessment. However, further improvements can be made by considering word sense disambiguation and identifying the specific product features on which the sentiment was expressed.

Kennedy et al., [8] introduced the concept of contextual valence shifters, which include negation, intensifiers, and diminishers. Intensifiers and diminishers alter the degree of the expressed sentiments. For example, "this movie is very good" is more positive than "this movie is good". The word "barely" in "the film is scarcely good" is a diminisher that makes the statement less positive. The researchers employed a term-counting method, a machine learning method, and a combination of both methods on the same dataset used in their experiment. They found that combining the two systems slightly improved the results compared to using machine learning or term-counting methods alone.

Polanyi et al. [9] introduced an algorithm that computes the sentiment scores of terms in a review, taking into account negations and intensifiers. The algorithm assigns a positive score of one and a negative score of -2 to words. Although the algorithm effectively handles negations and intensifiers, it has a limitation where it assigns the same score to two negative sentences.

The proposed work, Opine_Neg algorithm, aims to determine the sentiment of reviews, particularly those expressed on microblogging sites like Twitter. Users commonly express their views using positive and negative terms, intensifiers, and negation terms [11,12]. The proposed approach uses a tri-gram approach to determine rules based on negations, intensifiers, and opinionated terms. The system considers eight different rules to classify the semantic nature of the assessment. For example, if there are two reviews "This is a good bike" and "This is not a bad bike," both express positive polarity but the first review is more positive than the second. Opine_Neg aims to take this into account to produce a more reliable opinion insight.

III. OBJECTIVES OF THIS CONTRIBUTION

The majority of previous studies have addressed the aforementioned concerns independently when determining the opinion of reviews. This has prompted the development of a formulated model that incorporates emotion words, slang words, emoticons, negations, and intensifiers. The model labels text as favorable, unfavorable, or neutral. based on their polarity, identify pertinent features for detecting sentiment, and enhance the performance indicators like recall, F-Measure, accuracy and precision for tweets with positive, negative, and neutral sentiment.

The primary objective of this work is to address the challenges posed by negations, intensifiers, and emotion words. During pre-processing, there is no requirement to eliminate intensifiers and negations. If such words belong to the stop words category, the get_stop_words function of the Natural Language Tool Kit (NLTK) in Python can be utilized. The negation and intensifier dictionaries are manually constructed. Negations are significant in computational linguistics as they can reverse the polarity of sentiment. Words such as "no," "not," "none," "nor," "shouldn't," and others fall under the category of negation.The methodological diagram of the Opine_Neg approach is presented in [1].

IV. METHODOLOGY Of OPINE_NEG

The methodology of the proposed Opine_Neg technique is depicted in Figure 1.

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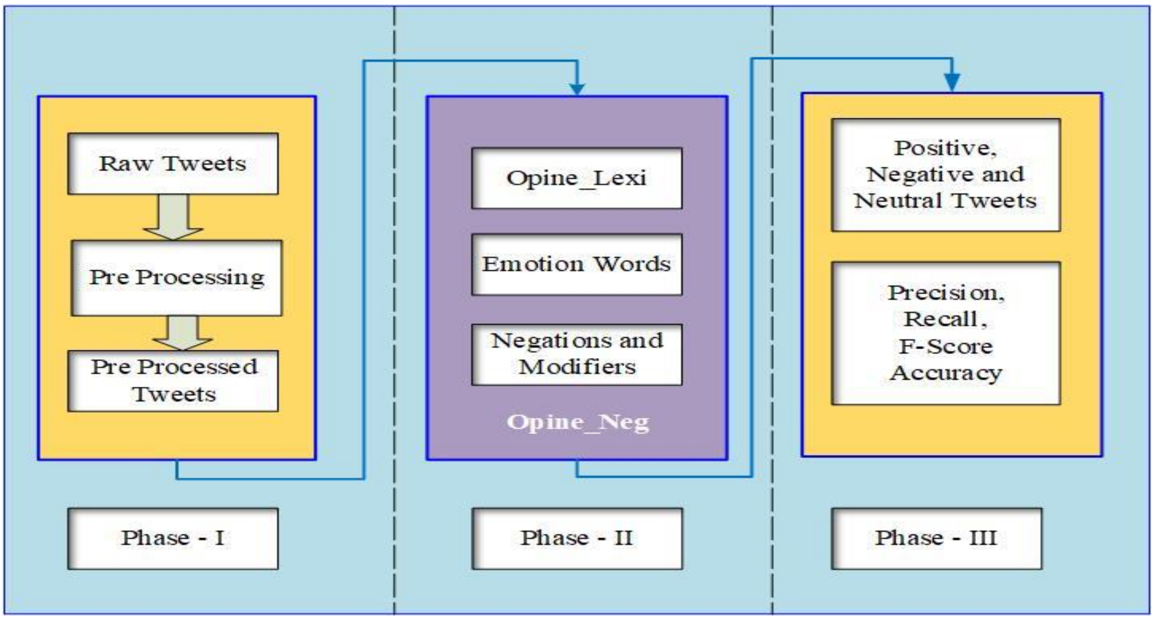

Figure 1 Work Flow Diagram of the Opine_Neg Approach.

- **Phase I: Tweets collection:** User reviews are collected from twitter using API.
- **Phase II: Opine_Neg approach** has been proposed to handle negations, Intensifiers and emotion words along with slang words & emoticons. To handle the negations and Intensifiers there are eight different rules formed and used.

Phase III: Opinion Classification: The favorable, unfavorable, or neutral tweets are classified. The widely adopted polarity measures such as like recall, F-Measure, accuracy and precision for tweets with positive, negative, and neutral sentiment [13] are calculated to measure the accuracy of the Opine_Neg approach.

5. Algorithm for Opine_Neg approach

The rules for the opine_Neg approach is presented in [1]. The Opine_Neg approach is demonstrates high efficiently for the classification and measuring the semantic nature of opinions. In the process, each tweet is taken for the process of classification. Opine_Neg approach executes and emphasizes on classification technique for the slang words, the use of acronyms and emoticons along with negation.

Procedure: Opine_Neg
Input: Microblogging Pre processed Reviews
Process: Handling Negation and Intensifiers
Output: Polarity of a Review
Negation Lexicon: List of Negation Terms (NL)
Intensifier Lexicon: List of Intensifier Terms (IL)
Records: For each row contains emotion words with tag and its score.
Pve_score: Positive Score, Nve_score: Negative Score, New_rec: New Record score
S(W): Sentiment word, POS: Part of Speech tag of a Word, Int_score: Intensifier Score
Neg_score: Negation score, DSD: Derivative Slang Dictionary, ASD: Acronym Slang Dictionary, SSD: Shortened Slang Dictionary, ED: Emoticon Dictionary,

```
Begin
Scan(s) from T
        For rec in Records:
                For r in Records
                        If□ pve_score >= nve_score
                                Score= Pve_score
                        Else
                                Score=Neg_score *(-1.0)
                        New_rec□ sum*S(W), POS, score);
//Slang words and Emoticon handling
For rec in new_rec:
        For r in RecordsL
                If(r € DSD v SSD v ASD v ED)
```

```
                    Perform opine_lexi();
// Intensifier Handling
        For rec in new_rec:
        For r in RecordsL
                If(r € IL)
                    IL_score = swap the sign of Int_score as subsequent adj;
// Negation Handling
        For rec in new_rec:
                For r in Records:
                    If (r € NL)
                        NL_score= swap the sign of Int_score and adj_score;
        For rec in NL_score
                Result = sum(S(W), IL_score, NL_score)
        SEM_SCORE= Opine_Lexi+Result    // overall semantic score
```

Figure 3. Procedure for Opine_Neg Approach

The cleaned data were input into the Opine_Neg technique, Let **T** be a tweet containing a sequence of words.. Basically unigram-based feature selection, which will split the word in single, and bigram-based feature selection split the terms in couple. So, Trigram based features are selected and applied on tweets, which consider sentiments, intensifiers and negation terms. Then tweets will be pre-processed and stored it in a document. Each record consists of sentiment, positive score, negative score and its POS tag. For each record, the comparison is performed whether the positive score of the term is greater than or equal to negative score of the term. If the positive score is greater the next step automatically takes the positive score otherwise negative score is taken for the next step. After allocation of scores slang, words and emoticons were handled using opine_lexi approach. It will check the word whether it is a slang word or not based on SWN. If the word exists in the SWN, it is not a slang word otherwise it is treated as slang word. If the founded sentiment word is a slang word opine_lexi approach, take the corresponding word from the dictionaries like. i.e., Derivative slang Dictionary, shortened slang Dictionary, acronym slang Dictionary and emoticon Dictionary. In addition, allocate the score using SWN classifier. Same way if emoticon is found in reviews it will approach the emoticon dictionary to get the equivalent meaning and score.

The intensifiers are identified using Part-of-speech tagging method. In a new record, intensifiers are occurring within a sentence it will be swapped by the sign of intensifier score as sign of next adjective. Similarly, Negations are found in record, it will swap the sign of intensifier and adjective scores as sign of negative scores. At the last, all the values will be summed up to calculate the degree of the opinion. If the intensity of the opinion score exceeds 0 it treated as positive sentiment. Intensity of the sentiment is less than 0 it labeled as negative. If the previous term is negation, this in turn leads to automatic revert the value that is multiplied by minus one. So, the sentiment orientation is changed from positive score into negative and vice versa.

VI. CONCLUSION

This paper presents a dictionary-based model for analysing the sentiments on tweets. A new approach called Opine_Neg proposed for handling the slang words and emoticons combinations with negations and intensifiers to provide improved accuracy compared to existing techniques. This paper also presents the effectiveness of the proposed Opine_Neg approach. The suggested method is implemented on the Twitter dataset. The proposed Opine_Neg achieved 81.08 % of accuracy in classifying the sentiments than the other methods.

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