Analyzing Internet Slang for Sentiment Mining

K. Manuel, Kishore Varma Indukuri, and P. Radha Krishna

***Abstract*—Every consumer has his own opinion about the product he is using which they are willing to share in social groups like forums, chat rooms and weblogs. As these review comments are actual feedbacks from customers, mining the sentiments in these reviews is being increasingly inducted into the feedback pipeline for any company. Along with it, the increasing use of slang in such communities in expressing emotions and sentiment makes it important to consider Slang in determining the sentiment. In this paper, we present an approach for finding the sentiment score of newly found slang sentiment words in blogs, reviews and forum texts over the World Wide Web. A simple mechanism for calculating sentiment score of documents using slang words with the help of Delta Term Frequency and Weighted Inverse Document Frequency technique is also presented in this paper.**

***Index Terms*—Sentiment Extraction, Internet Slang, Weighted Inverse Document Frequency, Classification.**

I. Introduction

THE web has dramatically changed the way people express their views and opinions. Sentiment analysis refers to the task of identifying opinions, favorability judgments, and other information related to the feelings and attitudes expressed in natural language texts. Slang is the use of highly informal words, abbreviations and expressions that are not considered as part of standard language. The surge of Computer Mediated Communications such as email, instant messaging, weblogs, chat rooms and short message service made usage of Internet slang almost ubiquitous. It has become very important to estimate opinion polarity of the sentiment oriented Internet slang present in the review.

Sentiment classification attempts to determine the type of sentiment (Positive or negative) in a given text. Sentiment classification has several important characteristics including the various tasks, features, techniques, and application domains. In this paper, we consider internet slang for sentiment classification. Then, we propose a method to determine the polarity of slang sentiment words.

The rest of the paper is organized as follows. Section II presents the related work and, we describe our approach to determine polarity of internet slang in section III. Section IV concludes the paper.

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II. Related work

Sentiment analysis can be conducted at various levels. Word level analysis determines the Sentiment Orientation (SO) of an opinion word or a phrase [5], [7], [8]. Sentence level and document level analyses determine the dominant or overall SO of a sentence and a document respectively [4], [6]. The main essence of such analysis is that a sentence or a document may contain a mixture of positive and negative opinions. Some existing work involves analysis at different levels. Specifically, the SO of opinion words or phrases can be aggregated to determine the overall SO of a sentence [4] or that of a review [1], [6], [11].

Most existing sentiment analysis algorithms were designed for binary classification, meaning that they assign opinions or reviews to bipolar classes such as Positive or Negative [1], [10], [11]. Some recently proposed algorithms extend binary sentiment classification to classify reviews with respect to multipoint rating scales, a problem known as rating inference [3], [6], [9]. Rating inference can be viewed as a multi-category classification problem, in which the class labels are scalar ratings such as 1 to 5 stars. A different line of research work in sentiment analysis algorithms aims at summarizing the opinions expressed in reviews towards a given product or its features [2], [4]. Such sentiment summarization also involves the classification of opinions according to their SO as a subtask, and that it is different from classical document summarization, which is about identifying the key sentences in a document to summarize its major ideas. To the best of our knowledge, there is no or little work exists in analyzing Internet Slang in assessing the sentiments from product reviews.

III. Internet slang sentiment analysis system

Given the opinionated document or piece of text which contains slang, our system is capable of (i) identifying sentiment oriented slang in the document, (ii) determining polarity score of each of slang word identified, and (iii) presenting the sentiment information it has garnered in some reasonable summary fashion. The solution approach proposed in this work can be divided into 3 steps. The First step is to classify the text into subjective and objective. The Objective sentences are filtered out and Subjective sentences proceed further. The Second step is to identify the sentiment slang from the subjective sentences. The Third step is to determine the polarity score of the slang word and compute the overall polarity of the text. The polarity of the slang is computed using Delta TF and weighted IDF measures as explained in the

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rest of the section. For illustration, we considered training data of documents as instances which are manually categorized into five different sets. These five sets correspond to the five “Set Types” mentioned in table I. For example, consider these sets to contain 10 reviews each. For each of the document in these sets, feature vector for subjective text is computed. The feature vector consists of one features for all the possible *n*-gram word combinations in these documents. For each of the document, traditionally, the frequency of occurrence of each of the word combination is recorded as the value for that feature. Weights for each of these features intuitively will be proportional to the probability of its occurrence in that particular set and will be inversely proportional to its probability of occurrence in the rest of the word document belonging to other sets. However, in our approach the value for each of the document is given by equation 2 as derived below.

If $f_{t,d}$ gives the corresponding features frequency in document d and if $|N|$ and $|P|$ are the total positive and negative corpus size, if N_t and P_t correspond to the effective number of documents containing t in the negatively and positively labelled sets, then the $V_{t,d}$, which is the value of feature t in document d, is given by:

$$V_{t,d} = f_{t,d} \times \log_2\left(\frac{|N|}{N_t}\right) - f_{t,d} \times \log_2\left(\frac{|P|}{P_t}\right) \tag{1}$$

Since our illustrative training sets are balanced, equation 1 becomes:

$$V_{t,d} = f_{t,d} \times \log_2\left(\frac{P_t}{N_t}\right) \tag{2}$$

The scores N_t and P_t, which are effective number of documents in positive and negative corpus containing term t is give by $((S_1 * 2) + S_2)$ and $((S_5 * 2) + S_4)$ respectively. Hence these metrics assign occurrences in stronger positive and negative corpus documents (documents in Sets S_1, S_5 respectively) twice the importance of the occurrence in corresponding relatively weaker documents (documents in sets S_2 and S_4). In many of the cases, a document sentiment score can be calculated by finding the difference of that words TFIDF scores in the positive and negative training corpora. If the score is greater than zero, then we can expect the document to be a positive opinion and otherwise if the score is less than zero, the document is expected to represent a negative opinion. This system can be easily extended to find the sentiment score of the newly discovered slang word or word phrase. If t represents the newly discovered slang word or phrase (i.e. the word t represents both the slang short form and the actual word phrase or word for the corresponding slang representation), the sentiment score for t can be calculated as:

$$Score = 2\left(\sum_{d\in S_5} V_{t,d} - \sum_{d\in S_1} V_{t,d}\right) + \left(\sum_{d\in S_4} V_{t,d} - \sum_{d\in S_2} V_{t,d}\right) \tag{3}$$

In the Equation 3, the first term represents the score component from the strongly positive and negative documents while the second term represents the scoring component from the relatively weak positive and negative documents. Sample results obtained for twenty slang words from the proposed method are shown in the table II.

TABLE I
SCORES FOR EACH OF THE SETS UNDER TRAINING CORPUS.

Set types	Score
+ve reviews with 5 star ratings (S5)	2
+ve reviews with 4 star ratings (S4)	1
Neutral reviews with 3 star ratings (S3)	0
−ve reviews with 2 star ratings (S2)	1
−ve reviews with 1 star ratings (S1)	2

Our term frequency transformation boosts the importance of words that are unevenly distributed between the positive and negative classes and discounts evenly distributed words. This better represents their true importance within the document for sentiment classification. The value of an evenly distributed feature is zero. The more uneven the distribution the more important a feature should be. Features that are more prominent in the negative training set than the positive training set will have a negative score, and features that are more prominent in the positive training set than the negative training set will have a positive score. This makes a clean linear division between positive sentiment features and negative sentiment features. As we are using five groups of training set, it leads to deeper polarity identification.

The illustrative training set consists of fifty cell phone reviews which are clustered manually into groups of five, four, three, two and one star. The training corpus built is taken from blogs and review websites like Mouthshut, Amazon and Epinions.

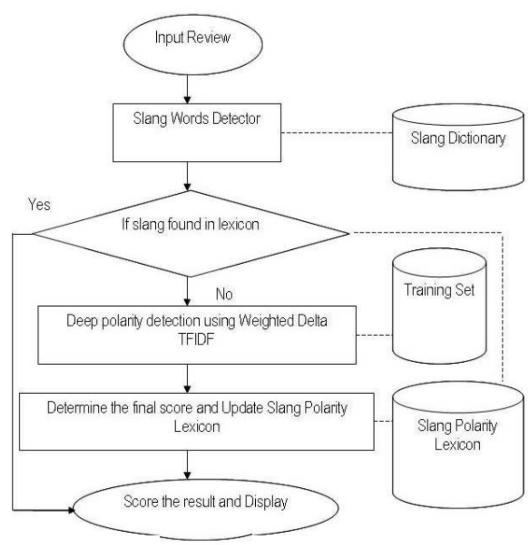

Figure 1. Flow Chart for determining Slang Sentiment.

IV. Discussion and Conclusions

In this paper, we developed an approach for handling Internet slang for sentiment analysis in blogs and review website. We also presented in this paper a method to compute sentiment scores for newly found slang words.

We first described identifying the slang words and their meaning, and proposed a method Delta TF and weighted IDF to weight the slang word score efficiently based on Delta TFIDF method. This approach showed better accuracy when compared to the flat term frequencies and TFIDF weights. The TFIDF measure boosts the impact of terms that are frequent among document belonging to a particular sentiment category while they are very rarely found in documents belonging to other sentiment categories. Since our data-set is composed from Internet slang sentiment documents, slang words like GMAB, H8, WOTAM, XLNT, GR8, AWSM, etc. tend to be used in a large number of these documents giving poor IDF scores. Additionally, these words have very low repetitions in any given document because authors spice up their reviews using synonyms to avoid boring their readers, resulting in low TF scores. In practice many SO slang words are generic and tend to have low TFIDF scores. We observed that the best analysis for this framework is unigrams. In our future work, we handle sarcastic sentences. While reading the entire blog, sarcastic sentences are perceived easily, but while analyzing the sentiments in the sentence level, they are hard to observe.

TABLE II
Polarity of 20 Slang Words

Sl. No.	Slang	Meaning	V	Polarity
1	AWSM	Awesome	2.484	+ve
2	AMZ	Amazing	2.907	+ve
3	GUD	Good	0.396	+ve
4	KOOL	Cool, Great	1.459	+ve
5	5N	Fine	1.000	+ve
6	XLNT	Excellent	4.322	+ve
7	N1	Nice one	2.322	+ve
8	SMEXY	Small and sexy	1.778	+ve
9	COMFY	Comfortable	0.232	+ve
10	GR8	Great	2.379	+ve
11	GMAB	Give me a break	-4.322	-ve
12	WOTAM	Waste of time and money	-4.585	-ve
13	H8	Hate	-1.193	-ve
14	DC	Don’t care	-1.00	-ve
15	SUX	Sucks	-0.848	-ve
16	DMN	Damn	0.000	Neu
17	NT	Not	-0.193	-ve
18	N/C	Not cool	-0.263	-ve
19	G4N	Good for nothing	-1.189	-ve
20	VFM	Value for money	3.414	+ve

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