User Reviews Data Analysis using Opinion Mining on Web

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***Abstract* — The web world is thriving with e-commerce these days and the need for online reviews has become crucial. The product reviews guide the customers and help them in making decisions regarding various available products which otherwise would bemuse them. But, one issue hampering this decision making problem is to sift through the huge jumbled piles of reviews available on the vast web. This makes the automatic extraction, summarization, and tracking of the available opinions very beneficial for the customers looking to buy a product. The automatic summarization and classification is different for different domains and varies with the testing situations.**

Through this paper, we are discussing usefulness of mining the customer opinions (i.e. opinion mining) and experimenting its viability in the mobile domain. Our implementation in mobile domain will be based on three main steps: 1) Applying Part-of-speech Tagging (POST), 2) Rule-Mining and identifying opinion words, 3) Summarizing and displaying the end results.

***Keywords*: Opinion mining, Sentiment Analysis, Online reviews, POS Tagging, Rules.**

I. INTRODUCTION

The World Wide Web is a progressive world constantly evolving with changing times and growing in terms of the data it has to offer. Earlier, the web content was dominated by read-only, objective views given out by the retailers but, with time, this factual information has been taken over by subjective views contributed by consumers themselves. The objective content is the factual data about a product/service that a business provides to a consumer. They generally have a positive or neutral annotation associated with them which sometimes sways the consumers from the product's/service's real-time experience. The subjective views are a collection of opinion, reviews, recommendations, comments, ratings and personal experience shared by different users communicated through forums, social networks, blogs, etc., along with the factual data (Pang & Lee, 2008). This publicly open collection of reviews is a boon for the consumers as they get to share and learn the different aspects of a product/service like features, advantages, limitations, suppliers. Due to all of the above, the transition from business-to-consumer communication to a peer-to-peer model has been a very important feature of the Web media (Kozinets, 1999).

The online peer-to-peer communication serves as a medium of spreading awareness regarding a product/service and targets a larger audience than any other medium. (Mudambi & Schuff, 2010). Different review sites provide different means of evaluating the product/service to the consumers. These means include thumbs up/down(indicating like/dislike), numerical star ratings, comments, etc. to convey their experience with the product/service with other prospective consumers. The consumers can access the review sites or other such forums to discuss and find solutions for product/service-related problems, for pre-purchase product inquiries, and post purchase service evaluations on an unprecedented scale in real time (Zhu & Zhang, 2010). Marketing literature has numerous indications and evidences that show that online product reviews and recommendations are useful for potential consumers in decision making process regarding the product choices and purchase decisions (Duan et al., 2008; Senecal & Nantel, 2004; Zhang & Tran, 2009) by providing a veritable source of product/service information (Sher & Lee, 2009).

This paper exploits the publicly available pool of online product reviews by automatically extracting marketing intelligence from the vast repository of user-generated opinions through 3 steps:

- ***Part-to-Speech Tagging(POST)*** – Identifying and categorizing words in a piece of text in a given language into defined parts of speech,
- ***Sentiment Analysis through Rule Mining*** - Inventing new methods, relations between two or more variables and categorizing words into positive and negative,

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- ***Output*** - Summarizing and displaying the end results.

In summary, this paper presents a novel application of existing automatic extraction, sentiment analysis and summarization techniques for product review annotation classification (i.e., to discover product as recommended/not-recommended in a review), product attribute popularity tracking, extracting aggregate positive vs. negative opinion. Our paper is organized as. Section 2 discusses different studies related with online reviews and sentiment analysis. Section 3 explains the methodology of the proposed work. Section 4 describes dataset used in the study and results. Section 5 discusses business implication of current work and conclusion.

II. RELATED WORK

This section provides literature review of the research streams related to eWOM such as online product reviews and sentiment analysis on product reviews.

A. Studies Related with Opinion mining and Sentiment Analysis on Online Reviews

User-generated consumer reviews assist other potential consumers to make well-informed decisions about a product/service and also help the business class to understand problems encountered by the consumers and their product weaknesses. For exploiting the vast source of online product reviews, various advanced text processing methods, automated tools and techniques based on opinion mining and natural language processing have been proposed in literature (Chung & Tseng, 2012).

Implementing these advanced tools and techniques on online product reviews may set a pattern for a larger consumer and business audience (Gamon, Aue, Corston-Oliver, & Ringger, 2005). Earlier research on exploiting the online product reviews are based on opinion mining and sentiment analysis for identifying whether the consumer recommends the product or not, whether the product features are supported well by the consumers or not.

Opinion mining and sentiment analysis comprises of machine learning (ML), information retrieval (IR), natural language processing (NLP), text mining and Web search techniques to detect, extract and summarize opinion, sentiment and subjective knowledge from vast amounts of user generated text content on web (Pang & Lee, 2008; Prabowo & Thelwall, 2009; Tang, Tan, & Cheng, 2009). From earlier studies, it was concluded that opinion mining and sentiment analysis are over-lapping concepts and both terms can be used interchangeably (Pang & Lee, 2008). Sentiment identification can be performed on 3 levels of granularity: document, sentence and feature level. The granularity to be used depends upon individual business requirements. In this section, we will analyse and summarize the related studies as per the three granularity levels of sentiment identification

1) Document-level sentiment analysis: Document-level sentiment analysis annotates subjective text documents with an overall sentiment polarity, for example determining whether a product review recommends the product or not. The underlying assumption is that each document conveys a single overall opinion about a particular object (Gamon, 2004; Kang, Yoo, & Han, 2012; Kennedy & Inkpen, 2006; Pang & Lee, 2004; Pang et al., 2002). In document level or arff file analysis we use supervised learning technique or unsupervised learning technique. Supervised learning technique as machine learning classifiers have shown good performance for sentiment analysis on different consumer review datasets. Bayes Theorem, Maximum entropy, K – nearest neighbor algorithm have display good performance (Annett & Kondrak, 2008; Cui, Mittal, & Datar, 2006; Sharma & Dey, 2012; Tan & Zhang, 2008; Zhang, Ye, Zhang, & Li, 2011).

Unsupervised learning technique approaches overcome certain weaknesses of supervised methods like long training time, overtraining, improved data set quality or performance, user time or efforts and need of proper quantity. The sentiment orientation of different phrases were computed based on statistics like point-wise mutual information (PMI) (Chaovalit & Zhou, 2005; Turney & Littman, 2002) or by using different sentiment dictionaries (Taboada, Brooke, Tofiloski, Voll, & Stede, 2011). The sentiment polarity of the phrases constituting the text was averaged to obtain the overall orientation of the text into positive or negative classes. But unsupervised learning technique best for small data set like selected number of reviews or data and performance poor as compare to supervised learning technique (Miao, Li, & Zeng, 2010).

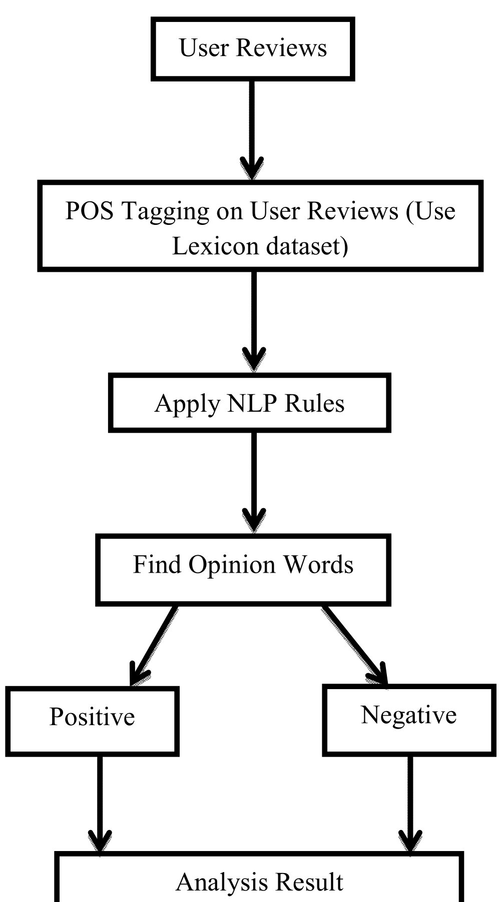
2) Sentence-level Sentiment Analysis: Sentence-level sentiment analysis assumes that different sentences might convey different opinion about the product. Sentiment analysis at sentence-level involves two subtasks. First, opinionated sentences are identified and separated from the text. The second subtask is to determine the sentiments orientation of a sentence as positive or negative (Klenner, Fahrni, & Petrakis, 2009). Both supervised and unsupervised

POS Tag	Abbreviations	Example
JJ	Adjective	Big
NN	Noun, singular or mass	Door
NNS	Noun, plural	Doors
RB	Adverb	however, usually, naturally, here, good
RBR	Adverb, comparative	Better
RBS	Adverb, superlative	Best
VB	Verb, base form	Take
VBD	Verb, past tense	Took
VBG	Verb, gerund or present participle	Taking
VBN	Verb, past participle	Taken
VBP	Verb, non-3rd person singular present	Take
VBZ	Verb, 3rd person singular present	Takes

learning methods have shown good performance for sentence-level sentiment classification (Khan, Baharudin, & Khan, 2010; Veselovská, 2012). Sentence-level sentiment analysis can be performed by taking an average or resultant sum score of the polarities of opinionated words presented in the sentence (Zhang, Narayanan, & Choudhary, 2010).

III. METHODOLOGY

The proposed research is completely experimental with a practical implementation described in detail. We use a software application developed in PHP language for our experiment.



A. POS Tagging

Part-of-Speech Tagging (POST) or lexical set are used to find out the grammatical words in any document or user speech: like noun, verb, adjective, etc. This can be done either on the basis of definition, e.g. all names are noun like India, or on the basis of context which depends upon the relationship with neighboring or similar words. Word classes is also known as POS tags. We use POS tags for specific sentence or task.

In Classical grammar classifies eight words for user text and user speech: Like Conjunction, the preposition, pronoun, noun, adjective, verb, adverb and interjection. Part of speech tags are basically assigned to particular task and particular user speech.

B. Rule Mining

Rule mining is a very well-known and well researched area for inventing new methods, relations between two or more variables. In this data mining technique, we can create new combinations, new rules, new methods based on the relations between parts of speech obtained from POS tagging. This can be done thorough study of the language and understanding the underlying relations between different parts of the speech and expressing these relations via rules.

Let us consider an example from the super market data. A rule defined as {Butter, Milk} -> {Bread} implies that if any user buys butter and milk together, he or she is likely to buy bread also. Such methods and rules are very useful for making good decisions. With the help of defined rules user can easily take any decision about any comment and hence about the product.

The extraction rules which we have created for our use in the mobile domain are as follows:

TABLE 1: ABBREVIATIONS FOR POS TAGS

NLP Rule
JJ -> NN or NNS or JJ or RB or RBR or RBS or VBZ
RB -> JJ
RBR -> JJ
RBS -> JJ
NN or NNS -> JJ or JJS or VBG or VBZ
RB or RBR or RBS -> VB or VBD or VBN or VBG
JJS -> NN or NNS

JJ or VBG or VBZ <- **NN**
RB <- **JJ**

1) Opinion Words: Opinions basically constitute people's thoughts, viewpoint, judgments, attitude, emotions, facts, statement about any particular product. These opinions when expressed through words of a particular language form *opinion words*.

Our implementation software identifies the words obtained from rule mining process as positive or negative. This is done by using a list of claimed negative and positive words. The list of positive words we use contains 2006 words and the list of negative words contain 4784 words. Examples for positive opinion words are successful, abundance, sharp, nice and examples for negative opinion words are abnormal, badly, careless, damage.

C. Orientation

Our implementation software displays the entire orientation of the user review being assessed. This is done on the basis of the number of opinion words found of either nature i.e. positive or negative. For e.g., if in a review we obtain 10 positive opinion words and 25 negative words then our review is recognized as a negative review.

IV. REVIEW MINING STEPS

In data web mining we used url to get reviews from popular e-commerce sites like www.flipkart.com, www.amazon.com, www.jabong.com and mouthshut.com. To get review content we used specific code to get data from each site as all of them use specific and different HTML tag to show their reviewers comment. This way we get only review's text to measure customer's opinion about the product.

One of the measure step in data mining is to find specific words which we can consider as opinion word. Its these opinion word which we consider to define particular review positive or negative.

Steps taken for data mining and to consider a particular review positive or negative:

- Take single review or site url and use POS tagging to grammatically recognize each word in the review.
- Before preceding any further remove all product name words from review words so that it doesn't affect our opinion words.
- Now with the words we got we can find words which we can consider as opinion words by using some specific opinion word extraction rules.
- Now find these opinion words in negative and positive words database to consider them as positive or negative and whichever is higher we consider that review as negative or negative.
- Number of words negative or positive found in review are then used to generate graph for that particular review.

V. EXPERIMENT RESULTS AND DISCUSSIONS

This section describes and demonstrates the implementation of our method on mobile reviews and the obtained results. We have used three ways to display the output of the analysis:

- *Orientation*: It gives the final inclination of the entire analyzed review. Also, it displays the identified opinion words from the review and each word's individual orientation through color coding.
- *Graph*: It gives a graphical representation of user reviews count of positive reviews and negative reviews opinion used in the review being considered.
- *Word Frequency*: It gives a graphical representation of the count of occurrences of the top 20 positive and top 20 negative words used in the reviews being analyzed.

In our experiment we have used the following three ways of analyzing the user content.

A. Single Review – Sentence-Level Analysis

This is used to analyze single user content and display its orientation. Figure 1 displays the default look of the 'Single Review' page.

Fig. 1 Default look of 'Single Review' page

The first step is to enter the review in the given 'Enter - Review' textbox. Figure 2 displays this step and in our experiment, we have taken the product review from www.flipkart.com although, any e-commerce or review site may be used for this purpose.

Fig. 2: Filled-in review

Now, user can see the output of the analysis through the above described methods by clicking on their respective buttons. Figure 3, 4, 5.1 and 5.2 display the above mentioned three ways of displaying the output respectively.

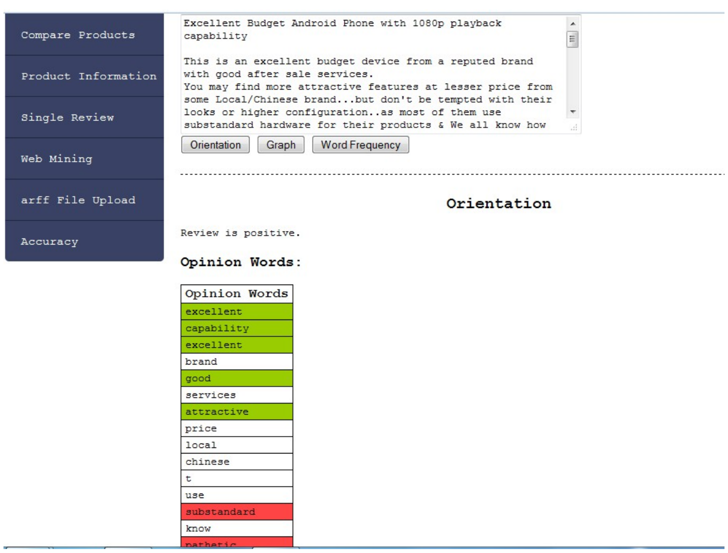


Fig. 3 Single Review Orientation with Opinion Words

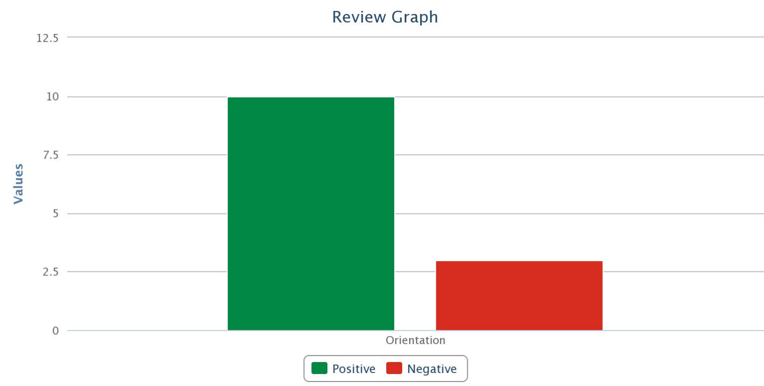


Fig. 4 Single Review Orientation Graph

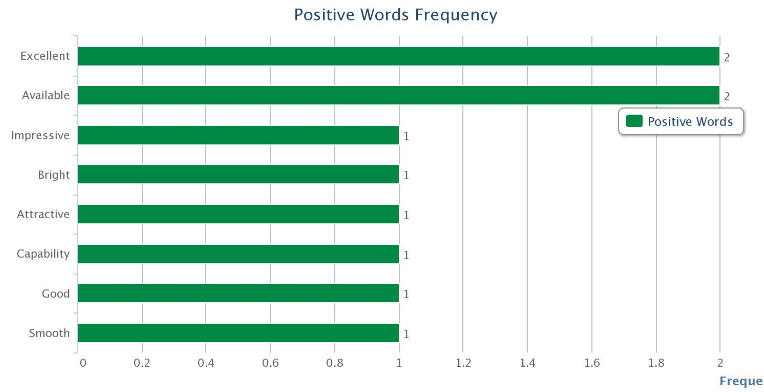


Fig. 5.1 Single Review Positive Word Frequency Graph

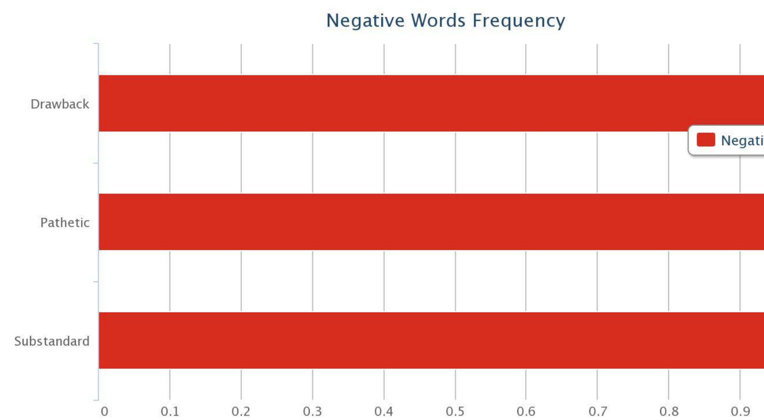


Fig. 5.2 Single Review Negative Word Frequency Graph

B. Web Mining

This is used to analyze user content from a specific product review url and display its orientation. Figure 1 displays the default look of the 'Web Mining' page.

Fig. 1 Default look of 'Web Mining' page

The first step is to enter the url of the review site in the given 'Enter URL' textbox. Figure 2 displays this step and in our experiment, we have taken the product review from http://www.flipkart.com/samsung-galaxy-s-duos-2-s7582/product-reviews/ITMDWZRBFZURSYUY?pid=MOBDQZPYAZSDKBWH&rating=3&otracker=pp_reviews_filters_3_stars , although, any e-commerce or review site may be used for this purpose.

Fig. 2 Filled-in URL

Now, user can see the output of the analysis through the previously described methods by clicking on their respective buttons. Figure 3, 4, 5.1 and 5.2 display the above mentioned three ways of displaying the output respectively.

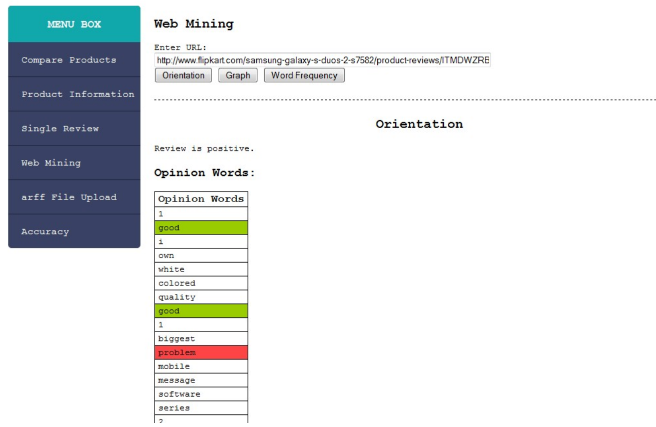


Fig. 3 Web Mining Orientation with Opinion Words

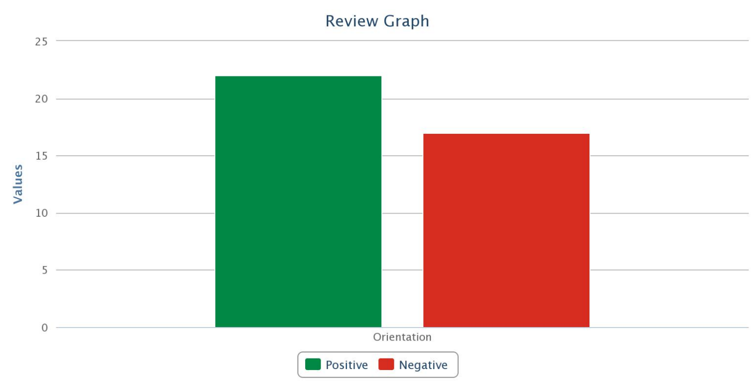


Fig 4 Web Mining Orientation Graph

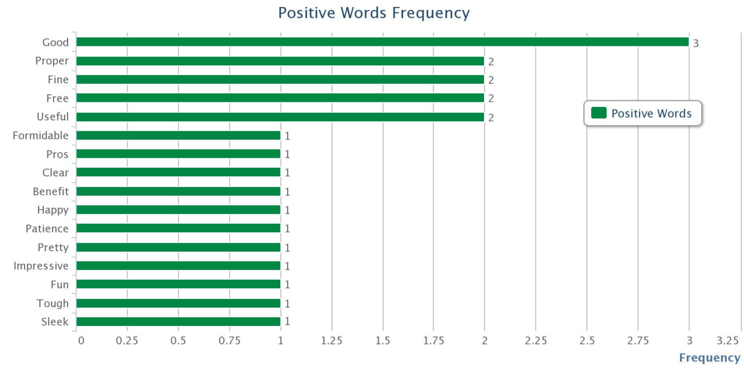


Fig. 5.1 Web Mining Positive Word Frequency Graph

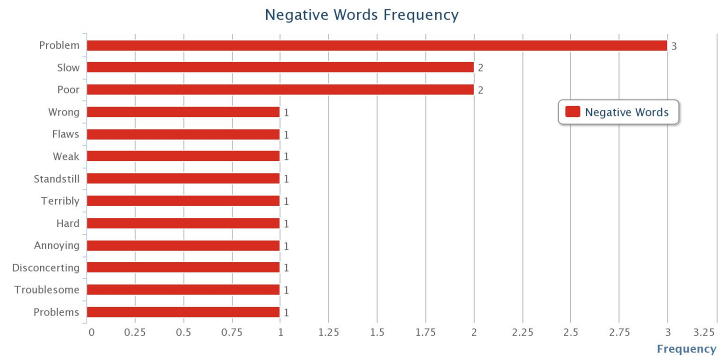


Fig. 5.2 Web Mining Negative Word Frequency Graph

C. Arff File Upload – Document-Level Analysis

This is used to analyze user content from an uploaded product review file with extension .arff and display its orientation. Figure 1 displays the default look of the 'Arff File Upload' page.

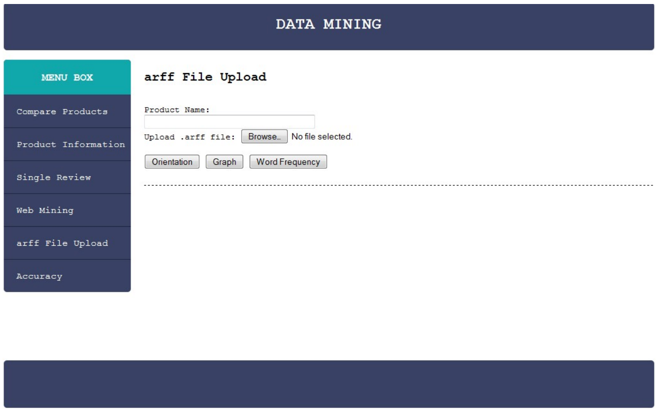


Fig. 1 Default look of 'Arff File Upload' page

The first step is to enter the product name in the given textbox, select the path of the product review file and upload it. Figure 2 displays this step and in our experiment, we have compiled the reviews from www.mouthshut.com, although, any e-commerce or review site may be used for this purpose.

Fig. 2 Filled-in product name and uploaded file

Now, user can see the output of the analysis through the previously described methods by clicking on their respective buttons. Figure 3, 4, 5.1 and 5.2 display the above mentioned three ways of displaying the output respectively.

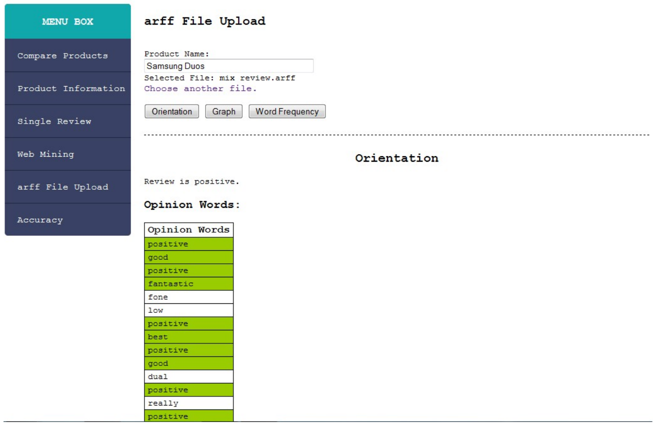


Fig. 3 Arff File Upload Orientation with Opinion Words

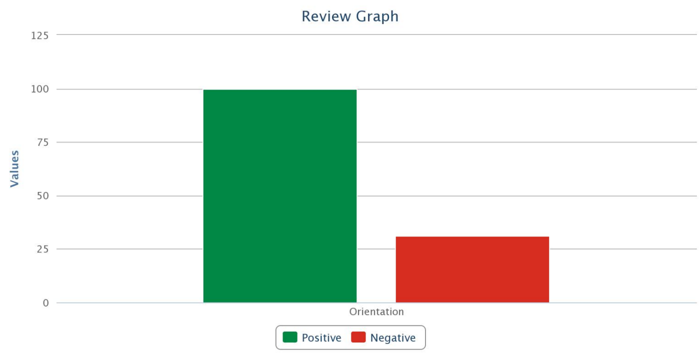


Fig. 4 Arff File Upload Orientation Graph

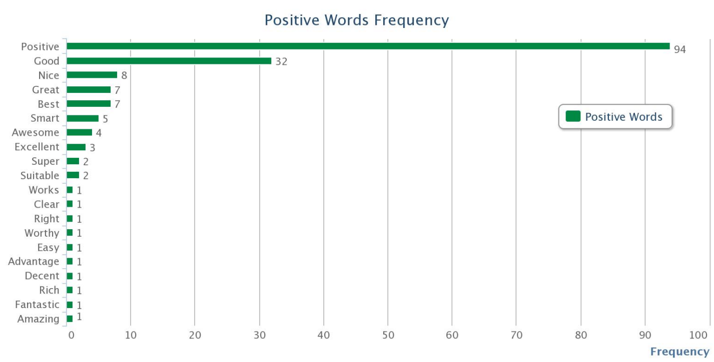


Fig. 5.1 Arff File Upload Positive Word Frequency Graph

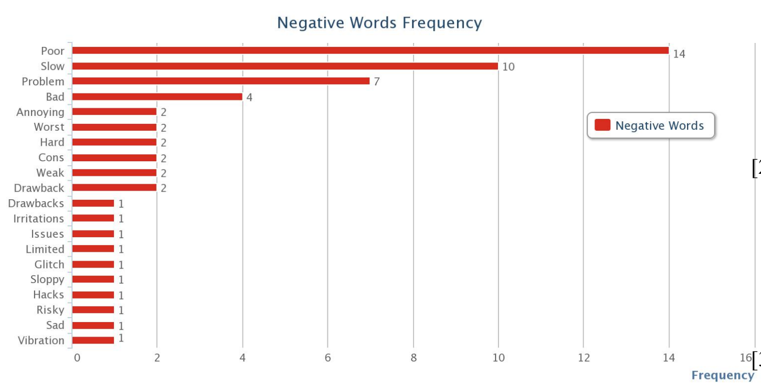


Fig. 5.2 Arff File Upload Negative Word Frequency Graph

VI. CONCLUSION

In our survey and implementation we study about the opinion mining and user sentiments. With user reviews we find out the consumer reviews and understand the sentiments. Sentiment analysis define user review is positive, negative and neutral. Sentiment analysis apply implementation apply on real scenario application like www.flipkart.com, www.mouthshut.com etc. Basically it is use for sentiment analysis. Sentiment analysis should be domain specific we are focusing on mobile domain. We can apply sentiment analysis on new domain like laptops, car and bike etc. Although this technique POS tagging and Rule mining used for sentiment analysis and we can find out the opinion words. With the help of this technique we can display graphical representation of opinion words and word frequency for positive or negative words. More future research could be dedicated to enhancement on this implementation. The recent work focuses on opinion mining and sentiment analysis on mobile domain. Our existing approach and method focus on: Orientation, Opinion Words, and Graphical representation, Word Frequency for positive or negative words.

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