Fine-grained opinion mining of product review using sentiment and semantic orientation

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Abstract: The reviews or feedback about a product or service has become quite significant in marketing, promoting, or improvising the product or service, since e-commerce, or purchasing of online products, has recently become a trend. The availability of product reviews is online and in the form of text but these reviews are very much in an unstructured form, which does not help either the new consumer, or the organisation, to take any decision further. In this paper, we have proposed an approach based on opinion mining and sentiment analysis. We have explored the sentiment orientation and sentiment classification to evaluate the customers' review. The reviews of various mobiles were converted from unstructured to structure to extract the summarised knowledge from online reviews. The number of user reviews was explored and the empirical results found that the sentiment orientation and classification provides the effective methods for better decision-making and benchmarking.

Keywords: online reviews, iphones, Semantic Orientation, Opinion Mining.

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1 Introduction

Sentiment analysis (Abdul-Mageed et al., 2011; Chen and Xie, 2008) also known as opinion mining (Ganapathibhotla and Liu, 2008; Jindal and Liu, 2008) refers to the use of natural language processing (Alm, 2011), text analysis and computational linguistics to identify and extract subjective information in source materials. Generally speaking, sentiment analysis aims to determine the attitude of a speaker or a writer with respect to some topic or the overall contextual polarity (Hassan and Radev, 2010) of a document. The attitude may be his or her judgment or evaluation affective state or the intended emotional communication that is to say, the emotional effect the author wishes to have on the reader. Opinions are central to almost all human activities because they are key influencers of our behaviours. Whenever we need to make a decision, we want to know others' opinions. In the real world, businesses and organisations always want to find consumer or public opinions about their products and services. Individual consumers also want to know the opinions of existing users of a product before purchasing it, and others' opinions about political candidates before making a voting decision in a political election. In the past, when an individual needed opinions, he/she asked friends and family. When an organisation or a business needed public or consumer opinions, it conducted surveys, opinion polls, and focus groups. Acquiring public and consumer opinions has long been a huge business itself for marketing, public relations, and political campaign companies.

With the explosive growth of social media (e.g., reviews, forum discussions, blogs, micro-blogs, Twitter, comments, and postings in social network sites) on the Web, individuals and organisations are increasingly using the content in these media for decision-making. Nowadays, if one wants to buy a consumer product, one is no longer limited to asking one's friends and family for opinions because there are many user reviews and discussions in public forums on the web about the product. For an organisation, it may no longer be necessary to conduct surveys, opinion polls, and focus groups in order to gather public opinions because there is an abundance of such information publicly available. However, finding and monitoring opinion sites on the web and distilling the information contained in them remains a sentiment analysis and opinion mining formidable task because of the proliferation of diverse sites. Each site typically contains a huge volume of opinion text that is not always easily deciphered in long blogs and forum postings. There are various ways to reduce the response time of queries asked online and offline like to use the concept of materialised views of data warehouse (Vijay Kumar and Devi, 2012; Vijay Kumar and Kumar, 2014, 2015; Vijay Kumar, and Haider, 2015). In materialised view the queries are first pre computed instead of a data warehouse. The average human reader will have difficulty identifying relevant sites and extracting and summarising the opinions in them. Automated sentiment analysis systems are thus needed. In recent years, we have witnessed that opinionated postings in social media have helped reshape businesses, and sway public sentiments and emotions, which have profoundly impacted on our social and political systems. The analysis of opinions may be topic-based (Vijay Kumar and Kumar, 2012) where documents are classified into predefined topic classes, e.g., science, sports, entertainment, politics etc. In topic-based classification topic-related words plays a significant role. However, in sentiment classification (Li et al., 2010a) they are least considered. Here, the classification is at document-level, where whole document is classified based on its polarity i.e., sentiment words that indicate positive or negative opinions (sometimes neutral) are important e.g., great, poor, excellent, bad, disgusting etc. This classification can also be extended to sentence level, comparative sentence (Jindal and Liu, 2006) i.e., to classify each sentence as expressing a positive, negative or neutral opinion. This paper presents application of existing sentiment analysis and opinion mining techniques for product review polarity classification (i.e., to discover product as recommended/ not-recommended in a review), product attribute buzz tracking, extracting aggregate positive vs. negative opinion (at different levels like company, brand, product or attribute), and product weakness identification. Our experimental results on mobile reviews demonstrate the effectiveness of our approach. The rest of the paper is organised as follows. 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 are reported in Section 5. Section 6 discusses conclusions of current work.

2 Related work

The work related to explore and mine the text data was started somewhere in early 2000, (Kennedy and Inkpen, 2006), some of work of sentiment detection began in late 1990s (Kessler et al., 1997; Spertus, 1997; Argamon-Engelson et al., 1998), but only in the early 2000s it become a major subfield of the information management discipline (Kobayashi et al., 2001; Raubern and Muller-Kogler, 2001). Most of the work has focused on various product reviews, there are applications to other domains such as debates (Thomas et al., 2006; Lin et al., 2006), news (Devitt and Ahmad, 2007) and blogs (Ounis et al., 2008).

Online reviews have also been used for automated market research to support the analysis and visualisation of market structure (Lee and BradLow, 2011). The study suggests that market structure analysis can be performed by automatically eliciting product attributes and brands' relative position from online customer reviews.

This kind of market structure analysis can facilitate analysis of product substitutes and complements. The detrimental effect of negative online product reviews on consumer-based brand equity is explored in a recent study that reported brand equity dilution by negative online WOM (Bambauer-Sachse and Mangold, 2011). A similar study on user generated content and consumer-based brand equity linkage explored how user-generated content affects brands (Christodoulides et al., 2012). The effect of third-party product reviews on financial value of firms introducing new products was also studied in a recent research (Chen et al., 2012). The results suggested that such reviews play significant roles in affecting firm value as the investors update their expectation about new product sales potential (Chen et al., 2012). Some recent studies have further suggested that the analysis of product reviews at different granularity levels can expose product attribute strength and weakness (Zhang et al., 2012) which in turn can explain specific preferences of each customer (Wei et al., 2010).

Dini and Mazzini (2002) studied customer views about a product from web and applied syntactic and semantic processing to these in order to provide a structured input from natural text, for later processing with data mining algorithms.

Liu (2011) proposed several techniques to mine various type of sentence from user reviews; their approach was based on the start work of Pang et al. (2002). They proposed several supervised and unsupervised techniques to mine various types of documents.

Hu and Liu (2004) proposed a work that was related to the analysing user comments and reviews of products sold online using Class sequential rule to extract features from pros and Cons of reviews, the main objective of their work was to extract opinion features that have been commented on by consumers.

Ferreira et al. (2008) gave a comparative study of feature extraction algorithms in customer reviews, the main focus of their work was on comparing two state-of-the-art algorithms for extracting features from product reviews based on the likelihood ratio test and on association mining.

Pang and Lee (2008) wrote a book that presents a thorough overview of the research in the field. Pang et al. (2002) conducted early polarity classification of reviews using supervised approaches. The techniques which they explored are support vector machines (SVMs), naive Bayes and maximum entropy classifiers; they used data sets with a different set of features, such as unigrams, bigrams, binary and term frequency feature weights and others. The outcome of their observation was that sentiment classification is not that easy than standard topic-based classification they also concluded that using a SVM classifier with binary unigram-based features produces the best results. Almost all the work on opinion mining from Twitter has used machine learning techniques. Pak and Paroubek (2010) aimed to classify arbitrary tweets on the basis of positive, negative and neutral sentiment, constructing a simple binary classifier which used n-gram and POS features, and trained on instances which had been annotated according to the existence of positive and negative emoticons.

Zaidan et al. (2007) introduced 'annotator rationales', i.e., words or phrases that explain the polarity of the document according to human annotators. By deleting rationale text spans from the original documents they created several *contrast* documents and constrained the SVM classifier to classify them less confidently than the originals. Using the largest training set size, their approach significantly increased the accuracy on a standard data set.

3 Research methodology

In this study, we have experimented with the mobile reviews datasets. The mobile reviews dataset was prepared by extracting mobile reviews of 20 different mobiles from various popular mobile review sites. The reviews written by consumers about mobiles were downloaded and analysed. The download was conducted during June 2013 to December 2013. After certain checks, a corpus of 1,000 user-generated reviews for 20 mobiles was obtained. The reviews were annotated by independent subjects and were classified in terms of the overall sentiment orientations as being positive or negative, and then divided to training and test datasets. The face validity of the text content was verified as per the response on five-star rating attached to the review. This study has annotated mobile reviews with more than three stars as being positive and mobile reviews with less than three stars as being negative by adopting an approach similar to those used in previous studies (Pang and Lee, 2004; Ye et al., 2009). However, we have discarded reviews with three stars (neutral) to restrict our work for binary sentiment analysis.

Three popular lexicons (sentiment dictionaries) have been used in this study. The first lexicon, known as the HM dataset, was proposed by Hatzivassiloglou and McKeown (1997). It contains 1336 adjectives: 657 positive and 679 negative words. The second lexicon is the GI dataset, which is a collection of labelled words extracted from the general inquirer lexicon (Stone et al., 1968). It includes 3,596 adjectives, adverbs, nouns, and verbs, out of which 1,614 are positive and 1,982 are negative. The opinion lexicon is adopted from Hu and Liu (2004) and it contains 2,006 positive and 4,783 negative subjective words.

3.1 Research objectives

To access the validity of data mining techniques (sentiment analysis and opinion mining) in mobile (telecom sector) for improving decision-making activities and to mine the unstructured text data for summarisation and identifying opinions from online reviews. To evaluate and explore the overall consumer online sentiments at various levels viz. feature and sentence level for effective decision-making activities.

3.2 Theoretical research model

Our approach for finding the semantic orientation and important feature from the text review is mostly experimental in nature involving practical implementation and empirical investigation of the proposed methodology. The basic methodology adopted in this paper for mining intelligence from online reviews using sentiment analysis approaches is depicted in Figure 1. The unstructured online reviews are crawled from the internet and are collected as opinionated text documents. The preliminary pre-processing and initial data cleaning removes any non-textual information like images, graphics or any other multimedia content.

Figure 1 Proposed methodology

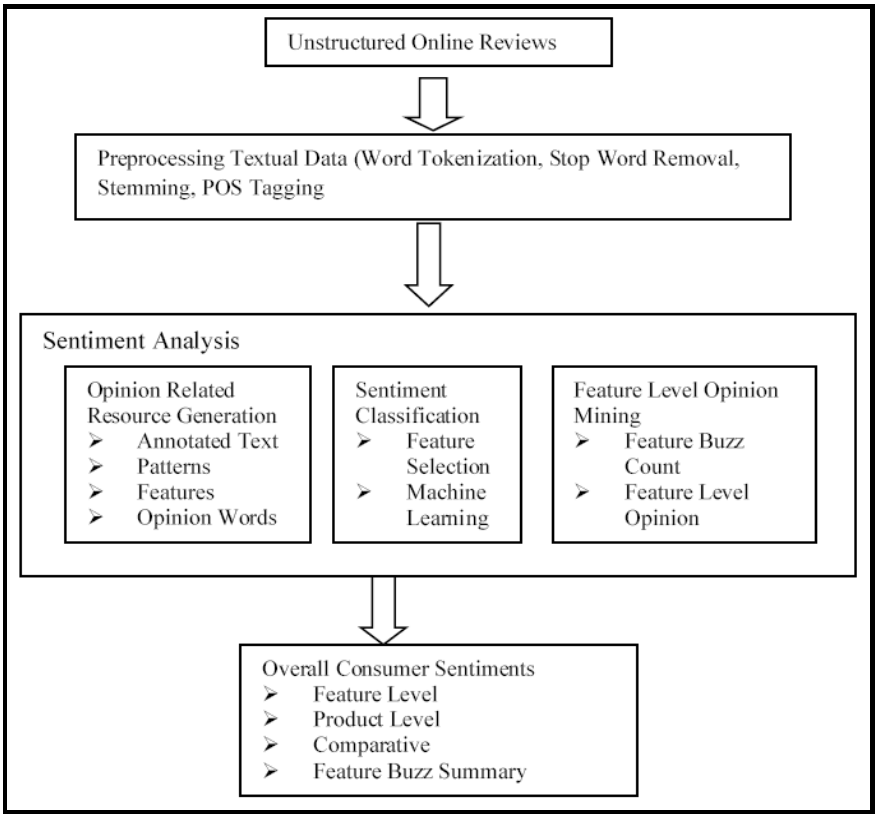


Figure 2 Sample review as input

The phone is great especially for web browsing and its so fast and quite easy to work. The only major bad thing about this phone is the battery life. With all the functions the phone has you want to use it all the time like a computer but battery life is so poor i have to have a battery charger on me all the time. It wont even last half a day if your using it alot. They should have made it thicker to add a bigger battery life. It needs to be doubled in order to be up to the standard of the phones capabilities.

Figure 3 Sample review as tagged

The_DT phone_NN is_VBZ great_JJ especially_RB for_IN web_NN browsing_NN and_CC its_PRP$ so_RB fast_JJ and_CC quite_RB easy_JJ to_TO work_VB ._. The_DT only_JJ major_JJ bad_JJ thing_NN about_IN this_DT phone_NN is_VBZ the_DT battery_NN life_NN ._. With_IN all_PDT the_DT functions_NNS the_DT phone_NN has_VBZ you_PRP want_VBP to_TO use_VB it_PRP all_PDT the_DT time_NN like_IN a_DT computer_NN but_CC battery_NN life_NN is_VBZ so_RB poor_JJ i_FW have_VBP to_TO have_VB a_DT battery_NN charger_NN on_IN me_PRP all_PDT the_DT time_NN ._. It_PRP wont_VBD even_RB last_JJ half_PDT a_DT day_NN if_IN your_PRP$ using_VBG it_PRP alot_NN ._. They_PRP should_MD have_VB made_VBN it_PRP thicker_JJR to_TO add_VB a_DT bigger_JJR battery_NN life_NN ._. It_PRP needs_VBZ to_TO be_VB doubled_VBN in_IN order_NN to_TO be_VB up_RB to_TO the_DT standard_NN of_IN the_DT phones_NNS capabilities_NNS ._.

The methodology proposed uses part of speech (POS) tagging (Hu and Liu, 2004) the main idea behind the approach is that each text contains numbers of words which fall in various POS categories. Each evaluative text is first converted into tagged input using Penn Treebank POS tags (Table 1) for example Figure 2 represents simple input and Figure 3 presents tagged input.

Table 1 Penn treebank POS tags

Tag	*Description*	*Tag*	*Description*
CC	Coordinating conjunction	PRP$	Possessive pronoun
CD	Cardial number	RB	Adverb
DT	Determiner	RBR	Adverb, comparative
EX	Existential *there*	RBS	Adverb, superlative
FW	Foreign word	RP	Particle
IN	Preposition or subordinating conjunction	SYM	Symbol
JJ	Adjective	TO	To
JJR	Adjective, Comparative	UH	Interjection
JJS	Adjective, superlative	VB	Verb, base form
LS	List item marker	VBD	Verb, past tense
MD	Modal	VBG	Verb, gerund or present particle
NN	Noun, singular or mass	VBN	Verb, past particle
NNS	Noun, plural	VBP	Verb, non-third person singular present
NNP	Proper noun, singular	VBZ	Verb, third person singular present
NNPS	Proper noun, plural	WDT	Wh-determiner
PDT	Pre-determiner	WP	Wh-pronoun
POS	Possessive ending	WP$	Possessive wh-pronoun
PRP	Personal pronoun	WRB	Wh-adverb

4 Textual pre-processing

The unstructured online reviews are processed with basic natural language processing techniques like word tokenisation, stop word removal, stemming and POS tagging. Tokenisation converts a stream of text into words, phrases, symbols, or other meaningful elements called tokens. Stemming is done to reduce words to their basic root or stem. Many of the semantically useless words are discarded in stop words removal but, we have preserved some useful sentiment expressing terms such as ‘ok’ and ‘not’. The POS tagging can be useful to find features that appear explicitly as nouns or noun phrases and sentiment bearing words that appear as adjective or adverbs in the reviews (Hu and Liu, 2004). After tokenisation, stemming and stop word removal, vector space model (VSM) is utilised in order to generate the bag of words representation for each document. The last pre-processing step included the computation of the frequencies of the residual tokens and arranging them as per their frequencies or occurrences in whole documents set.

4.1 Sentiment analysis

The sentiment analysis step is the core of the proposed methodology. Sentiment analysis aims to find what people like and dislike about a given object (product or service) and it involves retrieval of sentiments expressed in opinionated texts related to the object and its attributes. Therefore, finding the object features that people mention is an important step. The opinion related resource generation involves identifying product features (attributes), extracting the associated opinions (positive or negative) and annotating text documents for training the machine learning classifiers.

4.1.1 Extracting features and opinion words

This work has used only explicit features and opinions available in the online reviews. Any POS tagger like NL processor linguistic parser can be used to parse each sentence and tag each token in the sentence in order to extract high-frequency noun, adjective, verb and adverb phrases. Some key extraction rules based on NLP adopted from Miao et al. (2010) are given in Table 2 with some examples related to phone reviews.

Table 2 Patterns of tags for extracting two-words phrases from

S. no	*First word*	*Second word*	*Third word (not extracted)*
1	JJ	NN or NNS	Anything
2	RB,RBR, or RBS	JJ	Not NN nor NNS
3	JJ	JJ	Not NN nor NNS
4	NN or NNS	JJ	Not NN nor NNS
5	RB, RBR, or RBS	VB, VBD, VBN, VBG	Anything

Figure 2 represents the review of a mobile phone in which several features are mentioned by the author, this initial input text is termed as the evaluative text for which we have to find the semantic orientation. There are number of other features also which can be extracted from the review, Figure 3 is the transformed text this text is converted in this form by using Penn Treebank POS tags given in Table 1.

The main approach that we follow to extract the feature from the review is based on the fact that the combination of an adjective and noun mostly tells a description about that review. For example the *bigger battery*, *quiet easy*, *so fast* are some combination of words which represents some features from review. In Table 2 we are presenting such combination which will be helpful in extracting the features from the review.

This work has adopted redundancy pruning (Hu and Liu, 2004) to remove non-candidate and single word redundant features. Features having *p-support* (*pure support*) value less than 3 were removed. Pointwise mutual information (PMI)-based scores were used to group those having similar meaning or co-occurring features (Turney and Littman, 2002). PMI measures the degree of statistical dependence between two terms given in equation (1).

$$PMI\left(feature_1, feature_2\right) = \log_2\left(\frac{\Pr\left(feature_1 \wedge feature_2\right)}{\Pr\left(feature_1\right)\Pr\left(feature_2\right)}\right) \tag{1}$$

Here, the value in numerator of the log function is the co-occurrence probability of both features. The Pr(*feature*$_1$)Pr(*feature*$_2$) value represent the probability that the two features co-occur if they are statistically independent. Finally, *phrase similarity* is used to eliminate or merge similar product features (Miao et al., 2010). The similarity between two phrases is defined as the ratio of number of common words in two phrases to total number of unique words in both the phrases as given below:

$$phraseSim\left(feature_1, feature_2\right) = \left(\gamma_{common} \div \gamma_{unique}\right) \tag{2}$$

where γ_{common} is the number of common words and γ_{unique} is the total number of unique words in both features.

4.1.2 Sentiment-based classification of reviews

The sentiment polarity-based classification of online reviews will be useful to discover the overall opinion of the consumer and to judge the product as recommended/not-recommended in a review. This study has applied supervised machine learning-based approach for sentiment-based classification of online reviews as different studies have reported that machine learning techniques have performed better than semantic and lexicon-based methods of sentiment analysis (Pang and Lee, 2008). Recent studies have also confirmed that feature selection is beneficial for sentiment classification as it can reduce data dimensions to be considered by classifier for learning a model (Tan and Zhang, 2008). This paper has used Bayesian classification method, a SVM as machine learning model. To extract the aggregate opinion related to the feature, this work has used the sentiment lexicons-based approach which counts opinion bearing subjective words (mostly adjectives and adverbial phrases) associated with each feature. The sentiment lexicons comprise a dictionary of subjective terms along with their semantic orientations. First, we extract each subjective word associated with the feature appearing in any sentence of the online review. Then, the semantic orientation (sentiment polarity) of the opinion word is determined by using Bayesian classification.

5 Performance evaluation metrics

This research has used overall accuracy (OA) as performance evaluation metric. The confusion matrix shown in Table 3 has been used for evaluating the performance of classifiers.

Table 3 The confusion matrix

	Predicted positives	*Predicted negatives*
Actual positive examples	Total true positive examples (TP)	Total false negative examples (FN)
Actual negative examples	Total false positive examples (FP)	Total true negative examples (TN)

The performance of sentiment classification is evaluated by the OA as given in equation (3). Another popular evaluation metrics are precision, recall and *F*-measure which can be represented by ratios of entries from confusion matrix [given in equation (4), (5) and (6)].

$$\text{Overall Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

$$F\text{-Measure} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{6}$$

6 Experiment results and discussion

This section describes the experiment results of the study on mobile reviews. Figures 4 and 5 show performance of SVM classifier in term of recall, precision and OA on negative and positive reviews. SVM was trained and tested using radial basis function kernel with all other default parameters on the extracted features using information gain. The number of selected features was varied from very small to very large (100–4,000). All executions were validated using ten-fold cross validation by dividing the whole dataset into ten equal sized sets and training the SVM on nine datasets while, testing on remaining dataset. This process was repeated ten times so that the mean accuracy of all folds can be reported. SVM has given best accuracy around 80–81% for features selected in the range 300–2,000. The results indicate that we were able to classify the reviews as per their sentiment polarity with approximately 82% accuracy. The high precision for negative reviews and high recall for positive reviews confirms the complementary nature of classification for both the classes. The sentiment-based classification of mobile reviews in term of positive or negative can be helpful to judge overall opinion or attitude expressed by a reviewer about a phone, which can further be useful to find out whether the phone is recommended or not recommended in the review.

Figure 4 Sentiment classification performance for negative online reviews (see online version for colours)

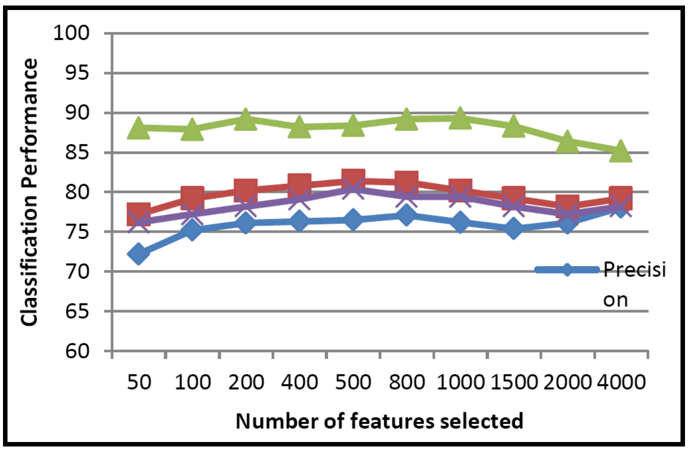


Figure 5 Sentient classification performance for positive online reviews (see online version for colours)

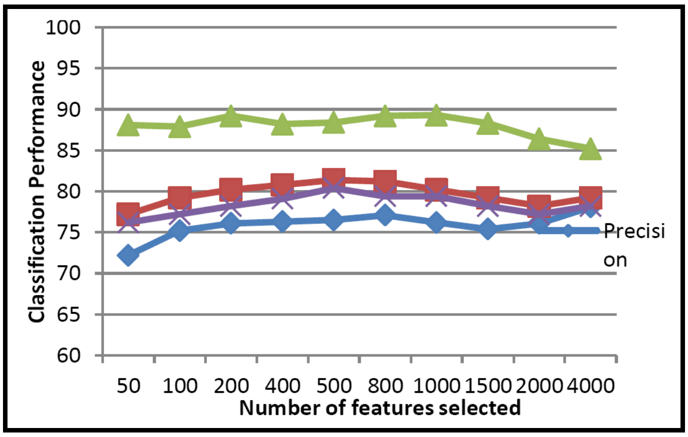
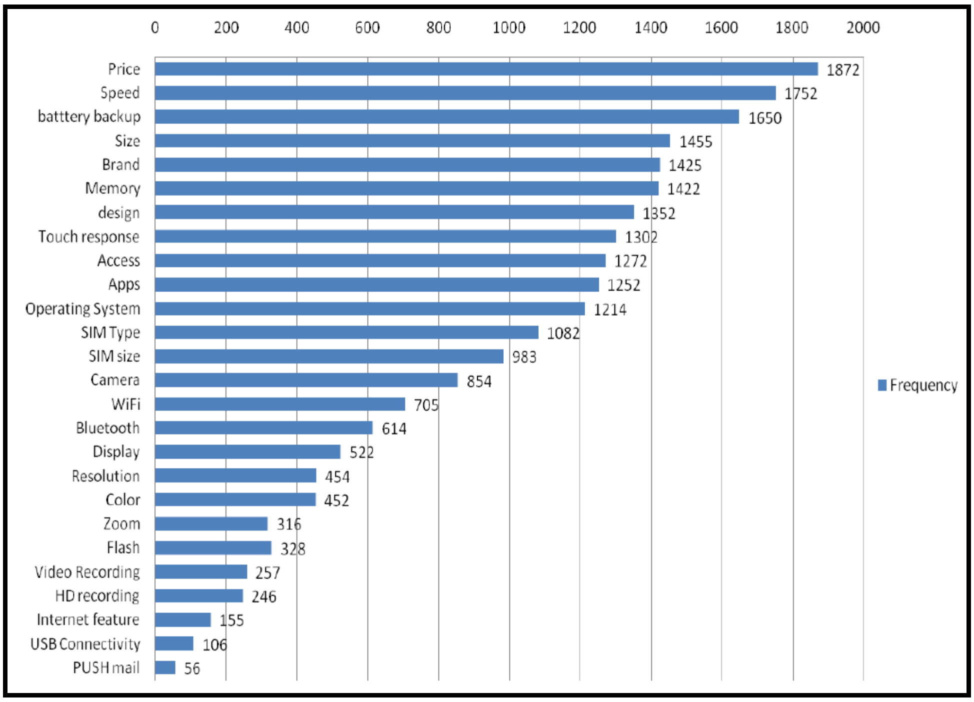


Figure 6 Representing feature buzz with top 26 (see online version for colours)



The feature-opinion tuple identification approach has accurately identified most common product features discussed by mobile consumers in the reviews. The extracted features are given in Table 3 with their associated frequencies. Figure 6 shows the feature buzz count graph for the top-26 most frequent features, which can be useful to find out which attributes are most important for the consumers. We can draw product and non-product related consumer associations from these results. We can see that after the price, processing speed is the next most frequent feature in mobiles in which consumers are most interested. The battery back up and size are the next topics, which consumers like to discuss and give their opinion.

Table 4 Top 50 frequent features extracted from 1,000 mobile reviews

Frequency	*Top 50 features extracted from mobile reviews*
More than 1,300	Price, processing speed, battery backup, size, brand, memory, design,
500–1,300	Touch response, access, apps, OS, dual sim, 3G, camera, Wifi, Bluetooth, FM,
100–500	Operating frequency, display, resolution, colour, zoom, weight, SIM type, SIM size, primary camera, secondary camera, flash, video recording HD recording, camera features, internet features, GPRS, USB connectivity
50–100	Tethering, recording, audio jack, music player, video player
< 50	Call memory, SMS memory, phone book memory, magnetometer, proximity sensor, ambient light sensor, accelerometer

Further, the opinion expressing pattern by consumers can be predicted by observing Figures 7 and 8.

Figure 7 Top 25 most frequent positive sentiment words in mobile reviews (see online version for colours)

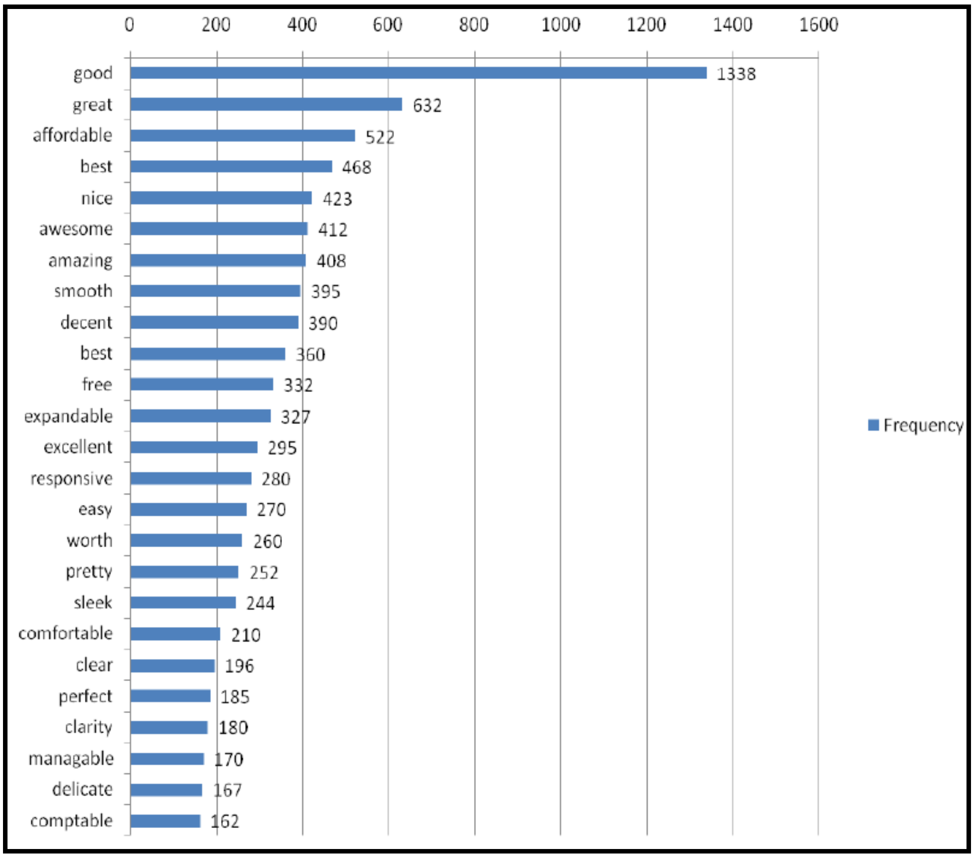


Figure 8 Top 25 most frequent negative sentiment words in mobile reviews (see online version for colours)

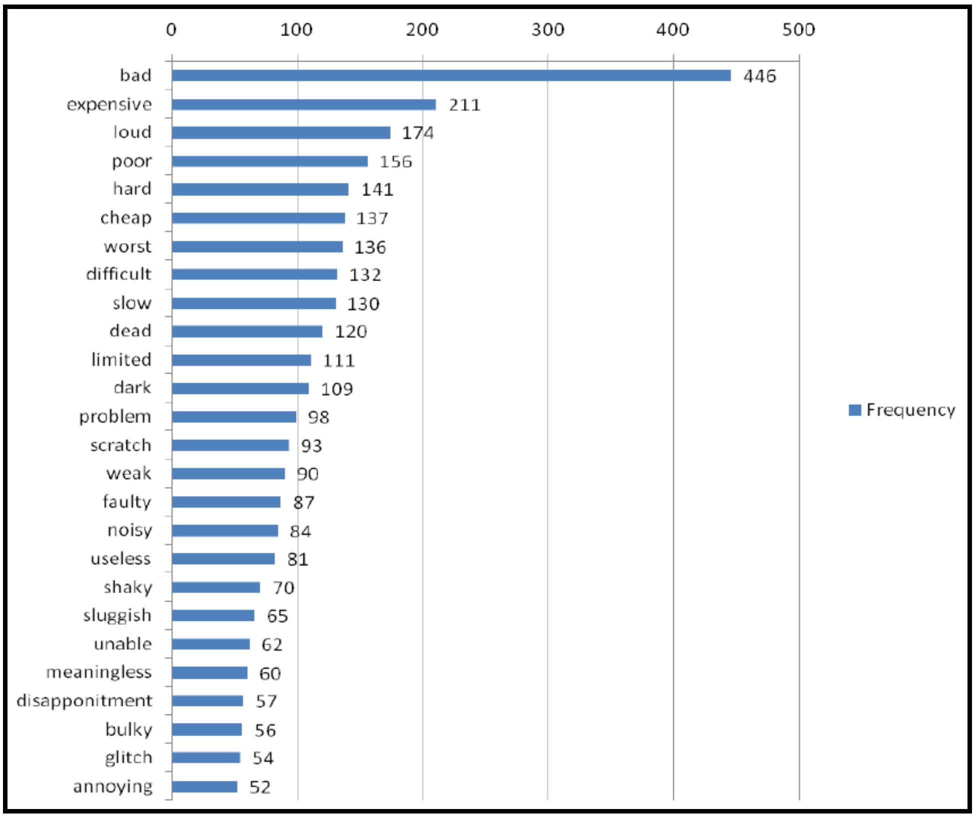
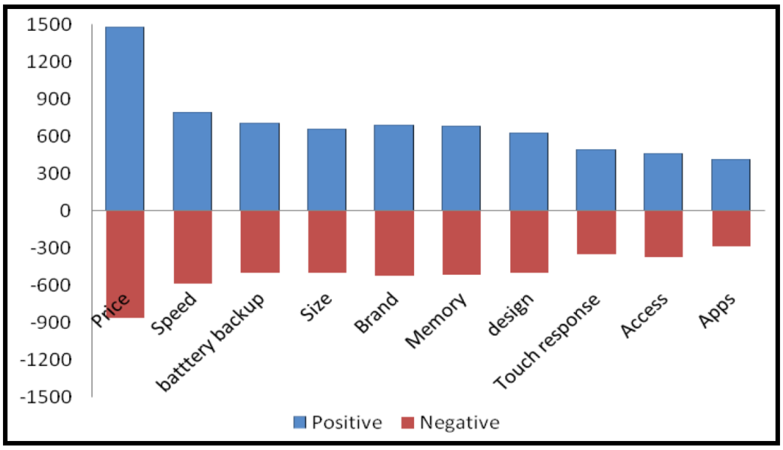


Figure 9 Overall positive and negative sentiment words used in feature-opinion tuple (see online version for colours)



We can see that consumers have expressed more positive sentiment words as compared to negative words related to top 10 most frequent mobile features (see Figure 9).

This study has efficiently extracted positive sentiment terms to create the ‘positive’ lexicon and negative sentiment terms to create the ‘negative’ lexicon specifically for the mobile domain. The Top 30 most frequent positive and negative sentiment words are represented in the Figures 7 and 8. The sentiment lexicons and their relative frequencies can be useful to quantify the sentiment strength related with different features. Fine-grained opinion mining allowed us to reveal, in the mobile consumers own generated content, what they liked and disliked the most about the mobiles in which they have used. Figure 9 shows consolidated positive and negative sentiment words used in feature-opinion tuple for top ten features. The Figure 9 gives us a snapshot of overall opinion related with each feature. We have shown only top ten features to maintain visibility, but more features can be included for a deeper analysis. Similar features of two different mobiles can be compared to find what consumers are saying in term of opinions for those similar features of competing mobiles or brands. This fine-grained opinion mining can be used to derive a feature’s weaknesses and perform product usage imagery analysis.

7 Conclusions and future scope

We can conclude that consumers use some most frequent positive words in large number in the positive reviews. At the same time, consumers use a large number of less frequent negative words in the negative reviews. This is also confirmed by retrieval of a rich negative sentiment lexicon with more words for negative opinion and smaller positive lexicon having highly frequent positive words. In summary, we can see that the proposed approaches are very promising, especially for overall review classification, feature buzz monitoring, fine-grained opinion mining and sentiment analysis resource generation. This study has used basic natural language processing and text mining approaches. However, there are some limitations in the existing approaches for feature and opinion extractions due to complex sentence structure and complex pronoun resolution. Pronoun resolution is a computationally expensive problem for real time sentiment analysis. The next section discusses conclusion of the studies related to online word of mouth.

In this paper we have proposed a method which is useful to finding the summarisation and orientation of a customer review. This research has demonstrated some methods for automatically extracting consumer opinions from online reviews on mobiles in India. Specifically, this study has attempted to incorporate sentiment analysis for deriving marketing intelligence from mobile review analysis. The current study provides an additional reason why, on the whole, online mobile reviews may benefit consumers and mobile companies and, suggests that potential conclusions can be drawn related to consumer behaviour by analysing mobile reviews. Whenever a company launches any new product or service, a large number of user opinions and reviews can be found on web. These reviews or feedback contains positive, negative or neutral opinions about service or product. The significance of this work is very useful in the sense that it can be used to learn the opinion of various product users and can be very useful from a organisation point of view. The decision-making process by a company can be enhanced if we know what is the expectation of our customer, which can be explored through opinion mining.

Our approach to opinion mining takes inspiration from a number of sources. It is most similar to the work of Turney (2002) in terms of technique. The approaches in sentiment analysis need to employ some more efficient strategies to deal with the linguistic issues imposed.

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