Sentiment Analysis of Mobile Reviews using Sentiwordnet

A dissertation submitted in the partial fulfillment for the award of Degree of

Master of Technology

In

Software Engineering

Submitted by

Gaurav Dudeja (2K12/SWT/06)

Under the esteemed guidance of

Dr. Kapil Sharma

DELHI TECHNOLOGICAL UNIVERSITY

BAWANA ROAD, DELHI

2013-2015

DECLARATION

I hereby declare that the thesis entitled "**Sentiment Analysis of Mobile Reviews using Sentiwordnet"** which is being submitted to the **Delhi Technological University**, in partial fulfillment of the requirements for the award of degree of **Master of Technology in Software Technology** is an authentic work carried out by me. The material contained in this thesis has not been submitted to any university or institution for the award of any degree.

Gaurav Dudeja

Department of Software Engineering

Delhi Technological University,

Delhi.

CERTIFICATE

Date: __________

This is to certify that the Major Project entitled "**Sentiment Analysis of Mobile Reviews using Sentiwordnet"** submitted by **Gaurav Dudeja** (2K12/SWT/06); in partial fulfillment of the requirement for the award of degree Master of Technology in Software Technology to Delhi Technological University, Bawana Road Delhi; is a record of the candidate's own work carried out by him under my supervision. The matter embodied in this thesis is original and has not been submitted for the award of any other Degree.

Dr. Kapil Sharma
Asst. Professor, Department of Software Engineering,
Delhi Technological University
Bawana road, Delhi - 110042

ACKNOWLEDGEMENT

July 2015

I would like to take this opportunity to thank my project guide Dr. KAPIL SHARMA for her invaluable and consistent guidance throughout this work. I would like to thank her for giving me the opportunity to undertake this topic. I am very appreciative of her generosity with her time, advice, data, and references, to name a few of her contributions. It is her wonderful association that enabled me to achieve the objectives of this work. I humbly extend my grateful appreciation to my friends whose moral support made this study possible.

Lastly, I would like to thank all the people directly and indirectly involved in successfully completion of this project.

Gaurav Dudeja

2K12/SWT/06

Master of Technology (Software Technology)

Delhi Technological University

Bawana road, Delhi – 110042

Table of contents

List of Figures

List of Tables

ABSTRACT

This paper presents our experimental work on a domain specific feature-based for aspect level sentiment analysis of mobile phone reviews. In decision making, the reviews of others have a important effect on customers to make their choices in regards to do online shopping, choosing products, etc. We devised an rule based domain independent scheme that analyses the textual reviews of a phone and assign a sentiment label on each aspect. The semantic score of subjective sentence is fetched from SentiWordNet Library to calculate their sentiments as +ve, -ve or neutral based on the textual sentence structure. We have used SentiWordNet library as a dataset with two different approaches of selections comprising of adverbs and verbs,adjectives and n-gram feature extraction. We also used our SentiWordNet library to compute the document level sentiment for each phone reviewed and compared its label with results obtained using Alchemy API. The sentiment label of a phone is also compared with the document level sentiment result. The results obtained show that our approach produces a more accurate sentiment label than the simple document level sentiment analysis.

Chapter 1

INTRODUCTION

Sentiment analysis is a language processing task that uses a approach to find textual content and categorize it as +ve or -ve. The unstructured matter knowledge on the net usually carries expression of opinions of users. Sentiment analysis tries to spot the expressions of opinion and mood of writers. a straight forward sentiment analysis rule tries to classify a document as 'positive' or 'negative', supported the opinion expressed in it. The drawback of document level sentiment analysis is basically as follows: Given a collection of documents [D], a sentiment analysis rule classifies every document [d D] into one among the 2 categories, +ve and -ve. +ve label denotes that the document d expresses a positive opinion and -ve label means d expresses a negative opinion of the user. additional refined algorithms try and establish the sentiment at sentence-level, feature-level or entity-level.

There are mainly three types of approaches for sentiment classification of texts: 1- By using a machine learning based text classifier -such as Naïve Thomas Bayes, SVM or kNN- with appropriate feature choice theme; (b) By using the unsupervised semantic orientation scheme of extracting relevant n-grams of the text so treated them either as +ve or -ve and consequentially the document; and (c) By using the SentiWordNet opensource used based online library that gives positive, negative and neutral scores for words. a number of the relevant past works on sentiment classification is found in [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11] and [12].

Now a days web of internet hosts an outsized volume of information created by numerous users. Users are currently co-creators of website, instead of being passive customers. The social media is currently a serious a part of the internet. The statistics shows that each four out of five users on the net use some sort of social media. The user contributions to social media vary from blog posts, tweets, reviews and photo or video uploads etc. an outsized quantity of the information on the net is unstructured text. Opinions expressed in social media in sort of reviews or posts represent a very important and attention-grabbing space price exploration and exploitation. With increase in accessibility of opinion resource product reviews, moive reviews, blog reviews, social network tweets, the new difficult task is to mine giant volume of texts and devise appropriate algorithms to know the opinion of others. This info is of very useful and informatial to firms that try and grasp the feedback regarding their product or services. This review helps them in taking user choices. additionally to be helpful for firms, the reviews and opinion strip-mined from them, is useful for users in addition. reviews about hotels in the city may helps a user going to a city seeking for a good hotel. Similarly, mobile phone reviews help other users to decide whether the phone is worth to purchase or not. Similarly, phone reviews facilitate different users choose whether or not the mobile phone is worth for money or not. during this paper we have got tried to explore a new SentiWordNet primarily based theme for each document-level and aspect-level sentiment classification. The document-level classification involves use of various linguistic options (ranging from Adverb+Adjective combination to Adverb+Adjective+Verb combination). we have got additionally devised a new domain specific heuristic for aspect-level sentiment classification of mobile phone reviews. This theme locates the self-opinionated text round the desired aspect feature in an exceedingly review and computes its sentiment orientation. For a mobile phone, this is used for all the reviews.

The sentiment scores on a particular aspect from all the selected reviews are then aggregated. This process is carried out for all aspects under consideration. Finally a summarized sentiment profile of the mobile phone on all aspects is presented in an easy to visualize and understandable pictorial form. The remaining report is organized as follow. Section 2 describes the approach of using SentiWordNet formulation for sentiment classification, along details of our implementation. Section 3 describes the dataset used in classification and performance metrics computed. Section 4 presents the results and the paper concludes with key observations in Section 5.

Chapter 2

LITERATURE REVIEW

The early work of sentiment analysis began with subjectivity detection, dating back to the late 1990‟s. Later, it shifted its focus towards the interpretation of metaphors, point of views, narrations, affects, evidentiality in text and other related areas. Shown below is the literature describing the early works of subjectivity and detection of affects in the text. With the increase in internet usage, the Web became a source of importance as text repositories. Consequently, a switch was slowly made away from the use of subjectivity analysis and towards the use of sentiment analysis of the Web content. Sentiment analysis is now become one of the dominant approach used for extracting sentiment from text and appraisals from online sources like websites and blogs. Separating non opinionated, neutral and objective sentences and text from the subjective sentences carrying many sentiments is a difficult job, however, it has already been explored earnestly in closely related yet separate field (J M Wiebe, 1994). It concentrates on the making of a distinction between "subjective" and "objective" words and texts, on one hand, the subjective ones provide evaluations and opinions and on the other hand, the objective ones are being used to present information which is factual (Wiebe, Wilson, Bruce, Bell, & Martin, 2004) (Wiebe & Riloff, 2005). This is quite different than sentiment analysis in regards to the set of categories into which the language units are classified by each of these two analyses. Subjective analysis focuses on dividing the language units into two categories; objective and subjective, where as sentiment analysis attempts to divide these language units into three categories: -ve, +ve and neutral. The area of concentration in some of the early studies was with subjectivity detection only (M. Wiebe, 2000). With the passage of time to time and a need for better understanding of system and extraction, momentum slowly increased towards sentiments classification and semantic orientations.

Like other development fields of research today, sentiments analysis is a terminology yet to be matured; moreover just attempting to define sentiment can be difficult to accomplish [14]. The words sentiment [13][15], polarity [11] [12] [17], opinion [19], [20], semantic orientation [12] [21], attitude [22] and valence [22] are used to represent similar if not the same idea. These words, more often than not, used either to make the reference to various aspects of one particular phenomenon, an example being [24] [14] where the sentiment is defined as an affective part of the opinion, or simply can be used as synonyms for each other without any true definition of their self. Furthermore, some of these sentences can be confusing because of their multiple synonyms already in linguistic tradition (ex. polarity, valence) and therefore are confusing. For our present study, the focus is on capturing expressed sentiment in a text as -ve, +ve or neutral; therefore, we will refer this domain of research as a sentiment analysis. Our preference is of using the term 'sentiment analysis' is due to the fact that: 1) the possibility of confusing this study with research in other areas is not likely because the term is not belong with any other research tradition, 2) the kind of data which was extracted from the text is accurately reflected [unlike in the case of opinions which could also possess a topical component], and lastly 3) it is parsimonious and precise [25] [26].

Recently, there is a change of attitude in the area of sentiment analysis whereby the concentration is now on classification, which has been added a third category known as neutrals [27], [16].it is no longer focused on the binary classification of only +ve/-ve [21]. Through observations, there came a realization that it is much easy to separate +ve elements from -ve ones than it is to differentiate +ves or -ves from neutrals. Majority of disagreements among the human annotators as well as the errors resulting from utilize the automatic systems are associated with attempting to separate the neutral words, sentences or text from those that are either -ve or +ve [16] . Moreover, a problem arises from the meaning attributed to the term 'neutrals'. This is because 'lack of opinion' [28] as well as 'a sentiment that lies between +ve and -ve [13] are both meanings of 'Neutrality' used in related literature. The latter definition is favored by sentiment analysis while the field of subjectivity analysis mostly use the previous interpretation. However, it is the latter meaning of the word that will utilized in this dissertation [25] [26].

A rating inference as a metric labeling problem was developed by [29]. They achieved this by first apply two n array classifiers, which can included one-vs.-all SVM and SVM regression, in order to classify these reviews in regards to multi point rating scales. After applying these classifiers, a metric labeling algorithm was utilized so that the results of the n array classifiers were completely changed in order to guarantee that the like items receive like labels. A similar function was determined from this. It is true that a typically used similar function in topic classification is the overlapping of terms however, when attempting to identify reviews having like ratings, it is not particularly effective [20]. The +ve Sentence Percentage (PSP) similarity function was subsequently introduced; which calculates the number of sentences which are considered +ve divided by the number of sentences in the review so that that are considered to be subjective. Results of experiments generally have shown an improvement in n-ary classifier performance when making use of metric labeling with PSP. Pang and Lee's work was later augmented by [30] where they used transductive semi supervised learning in their study. It is shown that classification accuracy could be improved upon with the help of reviews without user specified ratings, in other words, unlabelled reviews [28].

A kernel based regression algorithm which was introduced by [31] 2007, made use of order preferences of unlabelled data and it was successfully applied to thesentiment classification. The order preference of a pair of unlabeled data xi and xj indicates that xi is preferred to xj to some degree, even though exact preferences for xi and xj are unknown. For ex, in framework of sentiment analysis, when presented with the two reviews of unknown rating values, it is quite possible to determine which review is more +ve. They executed their algorithm with the rating inference problem. As a result, it was evidenced that by utilizing order preferences the performance of rating inference was much better than standard regression [25] [26].

Corpus based machine learning method or methods on compilations are able to compile lists of -ve and +ve words with a high accuracy of up to 95%. In order to reach their full potential, most of these approaches need immense annotated training datasets. Corpus based methods can overcome some of these limitations by utilizing dictionary based approaches since these approaches depend on existing lexicographical resources (such as Word-Net) to provide semantic data in regards to individual senses and words [32] [24] [24]. [31] suggested that when analyzing sentiment, semantical similar does not necessarily imply sentimental similarity. This suggestion was made on the base of statistical observations from a compilation of mobile phone reviews. Subsequently, a method for determining the semantic orientation of the opinion is proposed on the basis of relative frequency. An estimation of the opinion strength of a word and the semanti- orientation in regards to a sentiment class and its relative freq of appearance in that class is carried out using this methodology. For ex, if the word 'best' appeared 8 times in +ve reviews and 2 times in -ve reviews, its strength with respect to +ve semantic orientation is then 8/(8+2) = 0.8 [24].

Introduction of the new features, that are conceptually related to the key phrase frequency were done in [38]. On the basis of candidate phrases in the input document, these new features can be generated, by issuing the queries to Web search engines. An improvement in key phrase extraction has been experienced with these new although they are neither domain specific nor training intensive. The feature values are calculated from the number of hits for queries (the number of matching Webpages). A large collection of the unlabeled data, approximately 350 million Webpages without manually assigned key phrases, has been mined for the lexical knowledge to derive these new features. Simple methods for combining individual sentiments [37] and supervised [36] statistical techniques was proposed which can measure sentiment of the phrase or sentence level using opinion oriented words. Another popular method, proposed by [36], makes use of both lexical and syntactic features for the sentiment analysis and is a machine learning approach. This method, missed pertinent contextual information on which it indicates that the individual sentence itself is a vital when extracting semantic orientation.

An alternative method was suggested by [39] for utilizing WordNet's synonym relations for tagging words with Osgoods three semantic dimension. The shortest path of joining a particular word to the words 'good' and 'bad' was calculated through the WordNet relations in order to assign the values of +ve or -ve to the word. Dictionary based methods for sentiment classification at the word level have no need of large corpor, or search engines having special functionalities. Rather they depend on the readily available lexical resources existing today such as Word-Net. They are able to compile the comprehensive, accurate and domain independent word lists containing their sentiment and the subjectivity annotated senses. Such as a lists provide a vital resource for sentence or text sentiment classification and because of the early compilation they are able to increase the efficiency of sentiments classification at texts and sentence level. In contrast to other works this work presents sentence level lexical/dictionary knowledge base methods to tackle domain adaptability problem for different types data [34] [9].

Dictionary based techniques that make use of the data found in references and lexicographical resources, such as Word Net and the thesaurus in which can be used for assigning sentiments to a large number of words. Majority of such methods utilize the various relationships between the words (synonymy, antonymy, hyponymy / hyperonymy) in order to find seed words and other entries as described earlier. The data exists in dictionary definitions is made use in the wordlevel sentiment orientation in some of the recent methods. For semantic orientation lexical based semantic terms are extracted using dictionaries like Senti WordNet, Concept Net etc. for sentence level classification. According to [19]. The first try at employing Word Net relations in a word sentiment annotation was made by [16][17]. They made the suggestion about an extension to the lists of manually tagged +ve and -ve words by adding to the list the synonyms for those words. They began with just 56 verbs and 36 adjectives. The method was applied in 2 occurrences and acquired 6070 verbs and 12213 adjectives. Then on the basis of the strength of the sentiment polarity which had been assigned to each word, the words which has been acquired were ranked. This strength of-sentiment score or rank for each word was calculated by maximizing probability of the category of the word's sentiment in regards to its synonyms [26] [27].

Semantic characteristics, like word sentiment, of each word are greatly acknowledged as the good indicators of semantic characteristics of a phrase or a text that contains them, e.g. in (B. Baharudin, 2010) [21]. A sentence or text level sentiment annotation system that can uses words as indicators (features) of sentiment and therefore, It requires the creation of words lists annotated with sentiment markers. The research on word level sentiment annotation has been produced a number of such lists of words that were manually or automatically tagged as sentiment or classified as related to sentiment. [40]

[20] suggested a method that would use different information occurred at the same time in order to acquire words related to opinion (ex., disapproval, accuse, commitment, belief) from the text as a way to carry out analysis of subjectivity at the word-level. Two different techniques was used. The log likelihood ratio is computed with the first technique: using the data obtained by calculating how often the words obtained from one sentence occur with seed words taken from [50]. Relative frequencies of words found in documents, either subjective or objective, are computed by using second technique.

When NLP and statistical techniques are utilized, much importance is given to sentiment analysis at the word or feature level because it is an analysis of the text with the most detail.

The semantic orientation of a given phrase or a review word is determined by the techniques proposed by [18] and [41]. Several researchers used a preset seed word to enable extraction of opinion-oriented words and features [42] [43] and form a list used for semantic orientation, extraction and classification of opinion. Determining the polarity and subjectivity of a text is not the only aim of sentiment analysis. On the contrary, what the writer of the text specifically likes or dislikes regarding an object is also of importance [44]. Our main focus here is to discuss sentence and document level sentiment analysis. Sentence level analysis decides what the primary or comprehensive semantic orientation of a sentence is while the primary or comprehensive semantic orientation of the entire document is, handled by the document level analysis [13] [43]. Document level sentiment analysis deals with a document as a whole and classifies all the sentiments which have been expressed about a certain object by the author showing whether the overall document sentiment is +ve, -ve or neutral. However, the text document or review are split down into sentences for sentiment analysis to the sentence level. These sentences then evaluated by utilizing statistical or lexical methods in order to determine their semantic orientation. Three main steps are involved, namely Pre-processing, Text Analysis and Sentiment Classification. A compilation of specific reviews are taken as input by the model and are then processed according to the above three steps to obtain results. Review classification and evaluation of sentences or expressed opinions in the reviews are the results produced by the model. The machine learning method and topic classification are similar in the sense that topics are classes of sentiment such as Negative and Positive [14]. This is how it works: a review is broken down into phrases or words, the review is then presented as a document vector (bag-of-words model), and finally, the review is classified on the basis of the document vectors.

It is apparent that classifying a sentiment can easily be formulated as a supervised learning problem which has two class labels (negative and positive). In regards to the assumption above, it is not a surprise that the reviews utilized in existing research regarding data for training and testing are mostly product based. Data for training and testing is easily available due to any typical review site having already assigned a reviewer rating (e.g. 1-5 stars) to each review [45]. Commonly, a thumbs-up or positive review will be assigned 4-5 stars while a negative or thumbs-down review is assigned with only 1-2 stars. Studies present to date have taken unlabeled data from the domain of interest with labelled data from another domain as well as general opinion words and made use of them as features for adaptation[46] [12] [18].

In this thesis a technique for domain independent sentence level classification of sentiment is introduced [48]. Rules for all the parts of speech are applied so that this can be scored on the strength of the semantics, contextual valence shifter, and sentences structure or expressions on the basis of dynamic pattern match. However, word sense disambiguation to fetch accurate sense of the sentence has already been addressed. Opinion type, confidence level, strength and reasons are all identified using this system. Senti WordNet and Word-Net are utilized as the basic knowledge base which has the further capability of being strengthened by using these modifiers, information in the contextual valence shifter and all parts of the speech.

Chapter 3

SENTIMENT CLASSIFICATION

Sentiment characterization is an opinion mining movement concerned with figuring out what, if any, is the general feeling introduction of the sentiments contained inside of a given report. It is accepted all in all that the report being examined contains subjective data, for example, in such as in product reviews and feedback forms. Opinion introduction can be named having a place with contradicting positive or negative polarities – positive or negative criticism around an item, great or unfavorable sentiments on a point – or positioned by range of conceivable conclusions, for instance in phone from surveys with input running from one to five stars.

Supervised learning systems using different aspects of content as sources of features have been proposed in the writing. Early work seen in [13] presents a few supervised learning algos using bag of words features common in content mining research, with best execution obtained using support vector machines as a form of combination with unigrams. Grouping terms from a report into its linguistic parts, or role of speech has also been investigated: In [21] form of speech information is used as component of a feature set for performing assements of sentiments on a dataset of news wire articles, with similar methodologies attempted in [7], [10] and [16], on distinct data sets. On [20] a strategy that identifies and scores patterns in form of speech is applied to derive features for sentiment classification, with a comparible thought that applied to review extraction for product features seen in [4]. Separation of subjective and target sentences for the purposes of enhancing reports level sentiment classification are found in [14], where significant changes were obtained over a pattern word vector classifier. Other different studies concentrate on the correlation of composing style to overall sentiment, taking into the account that the use of colloquialisms and punctuation that may pass sentiment. In [22] a lexicon of colloquial expressions and a general expression rule base is to recognize detect unique opinion terms for example unusual spellings ("greeeat") and word combination ("supergood"). In [1] report statistics and features measuring aspects of composing style are joined with the word vectors to acuire considerable standards over a baseline classifier on a data set of phone reviews.

3.1 Opinion Lexicons

Opinion lexicons are assets that associate with words and sentiment orientation. Their utilization in review mining research originates from the theory that individual words can be considered as a unit of review information, and accordingly may give clues to reports sentiment and subjectivity. Manually created review lexicons were connected to sentiment classification as seen in [13], where a forcast of document polarity is given by count +ve and -ve terms. A similar methodology is presented in the work of Kennedy and Inkpen [10], this time utilizing an opinion lexicon based on the combination of other existing resources.

Manually created lexicons however have a tendancy to be constrained to a little number of terms. By its tendency, building manual lists is a period consuming effort, and may be liable to annotator bias, To overcome from these issues lexical induction methodologies have been proposed in the writing with a view to extend the size of sentiment lexicons from a core set of seed terms, either by investigating term connections, or by calculating similarities in report corpora. Early work in this area that is seen in [9] expands a list of +ve and -ve adjectives by assessing conjunctive statements in a report corpus. Another basic approach is to get opinion terms from the WordNet database of terms and relations [12], regularly by looking the semantic connections of a term such as equivalent words and antonyms.

3.2 WordNet Glosses and SentiWordNet

As noted in [15], term connections in the WordNet form of database create a highly disconnected graph, and along these expansions of sentiment data from a core of seed words by looking there semantic relationships such as there meanings and antonyms is bounded to be restricted to a subset of terms. To defeat this issue, data contained in term glosses – informative content going with every term – can be investigated to gather term, based on the presumption that a given term and the terms contained in its gloss are likely to demonstrate the same polarity. In [2] a strategy for lexicon expansion is proposed where terms are assigned +ve or -ve opinions based on the presence of terms known to carry opinion content found on the term gloss.The creators those argue that the glosses contains potentially low level of noise since they “are intended to match as close as possible as expected by the components of meaning of the word, have generally standard style, language and syntactic structure”; This thought is additionaly seen in [5], this time by utilizing managed learning systems for extending a lexicon by investigating gloss data, yielding +ve accuracy enhancements over a gold standard in compare to some portion of techniques previously discussed in this article. This is the same methodology utilized on building the SentiWordNet opinion lexicon [6].

SentiWordNet is built in a two-stage approach: first is, WordNet term connection such as antonym,synonym and hyponymy are investigated to extend a core of seed words used in [19], and known earlier to carry +ve or -ve review bias. After a fixed number of cycles, a subset of WordNet terms is acquired with either a +ve or -ve label. These term's are then used to prepare a committee of machine learning techiques. To minimize bias, the classifiers are prepared using diverse alogs and different training sets size. The predictions from the classifier committee are then used to determine the sentiment orientation of the remainder of terms in WordNet. The table below compares the coverage of SentiWordNet in relation to other assume built opinion lexicons accessible in the literature.

Opinion Lexicon	Total Sentiment Bearing Terms
General Inquirer (1) [17].	4216
Subjectivity Clues Lexicon [21].	7650 (out of 8221 terms)
Grefenstette et al [8].	2258
SentiWordNet [6].	28431 (out of total 86994 WordNet terms)

Table 1 Coverage of Opinion Lexicons

3.3 Web Crawling using HTML AGILITY PACK

To parse HTML from a website is otherwise called Screen Scraping. It's a process to access external website information (the information must be public – public data) and processing it as required. For instance, if we want to get the average ratings of Nokia Lumia 1020 from different websites we can scrap the ratings from all the websites and calculate the average in our code. So we can say, as a general “User” what you can have as “Public Data”, you'll be able to scrap that using HTML Agility Pack easily.

3.3.1 Background

Previously it was harder to scrap a website as the hold DOM elements used to be downloaded as string. So it wasn't a pleasure to work with strings and find out individual nodes by iterating through at and matching tags and attributes to specify your requirements. Gradually the way has improved and now it has become too easy using HtmlAgilityPack library. That's why this article will give you a simple demonstration on how to start with HAP.

You need to have the basics of programming and must know writing code in C# and ASP.NET.

3.3.2 How it works

Before HTML Agility Pack we had to use different built-in classes in .NET Framework to pull out HTML from a website. But now we don't have to use such loads of classes rather we'll use the HAP library and order it to do the task for us.

It's pretty simple. Your code will make an HTTP request to the server and parse/store the returned HTML.

First HAP creates a DOM view of the parsed HTML of a particular website. Then it's really some lines of code that will allow you to pass through the DOM, selecting nodes as you like.

Using an XPath expression, HAP also can give you a specific node and its attributes. HAP also includes a class to download a remote website.

Chapter 4

ALGORITHMIC FORMULATION

We have primarily based our classification formula on the publically avaiable library SentiWordNet [38]. The SentiWordNet approach involves getting sentiment score for every opinion containing term of the text by a search in its library. during this lexical resource every term t occurring in WordNet is associated to a few numerical scores obj(t), pos(t) and neg(t), describing the target, positive and negative polarities of the term, severally. These 3 scores square measure computed by combining the results created by eight ternary classifiers. to create use of SentiWordNet we want to initial extract relevant narrow terms and so search for his or her scores within the SentiWordNet. Use of SentiWordNet needs tons of selections to be taken relating to the linguistic options to be used, deciding what quantity weight is to be to every linguistic feature, and therefore the aggregation technique for consolidating sentiment scores. we have got enforced the SentiWordNet primarily based algorithmic formulation for each document-level and aspect-level sentiment classification.

4.1 Document-level Sentiment Classification

The document level sentiment analysis try to analyise the full document (such as one review) into '+ve' ,'-ve' or neutral class. The methodologies based on SentiWordNet focuses the term profile of the document and concentrate terms having desired POS label (such as adjectives, adverbs or verbs). This obviously shows that before applying the SentiWordNet based formulation; the review text should be applied to a POS tagger which tags each term occurring in the review text. At that point some chose terms (with wanted POS tag) are removed and the opinion score of every extricated term is gotten from the SentiWordNet library. The scores for every removed term in a review are then accumulated utilizing some weightage and accumulation plan. Subsequently two key issues are to choose (a) which POS labels ought to be separated, and (b) how to choose the weight age of scores of distinct POS labels extricated while registering the total score.

We have investigated with diverse linguistic highlights and scoring plans. Computational Linguists propose that modifiers are great markers of reviews. Case in point, if a review sentence says "The phone is incredible", then utilization of modifier "incredible" lets us know that the phone was loved by the analyst and perhaps he had a nice experience by utilizing it. At times, Adverbs further adjust the sentiment communicated in audit sentences. Case in point, the sentence "The phone is extremely good" communicates a more +ve supposition about the phone than the sentence 'the phone is great'. A related past work [12] has additionally inferred that 'Adverb + Adjective' consolidate creates preferred results over utilizing modifiers alone. Subsequently we favored the 'adverb + adjective' consolidate over removing 'descriptive word' alone. The adverbs are usually used as complements or modifiers. Few more examples of this usage are:- he ran quickly; only adults; very dangerous trip; very nicely; rarely bad; rarely good etc. In all these examples adverbs modify the adjectives. Though adverbs are of various kinds, but for sentiment classification only adjectives of degree is useful.

Some past works have recommended misusing the "verb" POS labels in addition to 'adjective' for sentiment classification. Here, we have investigated with two semantic highlight determination plans. In one we only concentrate on 'adjectives' and any 'adverbs' going before the selected adjective. In the other one we seperate both 'adjectives' and 'verbs', along with any 'adverbs' going before them. Since, adverbs are changing the scores of succeeding terms, it needs to be chosen as to what extent the sentiment score of an 'adverb' should change the succeeding 'adjective' or 'verb' sentiment score, to obtain higher accuracy. We have chosed the modifying weight age (scaling factor) of adverb score as 0.35, in view on the conclusions reported in [14] and [11]. The other fundamental issue that remains to be addressed is how should the sentiment scores of chosed 'adverb+adjective' and 'adverb + verb' consolidated be aggregated. For this we have attempted different factors of weight ranging from 10% to 100%, i.e. the 'adverb + verb' scores are combined to 'adverb + adjective' scores in a weighted way.

In the first plan of utilizing only 'adverb + adjective' join, we have picked a scaling element of = 0.35. This is proportionate to giving just 35% weight to adverb scores. The changes in adjective scores are thus in a fixed proportion to adverb scores. Since we picked a value of scaling variable sf = 0.35, the adjective scores will get a higher priority in the consolidated score. The demonstrative pseudo-code of key steps for this plan i.e. Senti-WordNet (AAC) is illustrated below. Here AAC refers to Adverb + Adjective Combinations.

Fields	Descriptions
POS	Part of speech linked with synset. This can take four possible values: a = adjective n = noun v = verb r = adverb
Offset	Numerical ID which associated with part of speech uniquely Identifies a synset in the database.
PosScore	Positive score for this synset. This is a numerical value ranging from 0 to 1.
NegScore	Negative score for this synset. This is a numerical value ranging from 0 to 1.
SynsetTerms	List of all terms included in this synset

Table 2 SENTIWORDNET DATABASE STRUCTURE

For each sentence, extract adv+adj combines.
For each extracted adv+adj combine do:

- ❖ If adj score=0, ignore it.
- ❖ If adv is affirmative, then
  - ➢ If score(adj)>0
    - ♦ fsAAC (adv,adj)= min(1,score(adj)+sf*score(adv))
  - ➢ If score(adj)<0
    - ♦ fsAAC (adv,adj)= min(1,score(adj)- sf*score(adv))
- ❖ If adv is negative, then
  - ➢ If score(adj)>0
    - ♦ fsAAC(adv,adj)= max(-1,score(adj)+sf*score(adv))
  - ➢ If score(adj)<0
    - ♦ fsAAC(adv,adj)= max(-1,score(adj)- sf*score(adv))

Here, adj refers to adjective and adv refers to adverb. The last sentiment values [fsAAC] are scaled form of adverb and adjective Senti-WordNet scores, where the adverb score is given 35% weightage. The presence of 'Not' is taken care by subtracting the scores obtained. Firstlyl we picked the sentence boundaries of a review and then we process all those sentences. For every sentence we choose the adv + adj combines and then compute their sentiment scores according the scheme described in the 723 pseudo code. The final document sentiment score is an addition of thise sentiment scores for every sentence occurring in it. The score value decided the polarity of the review.

The second usage that we attempted joins both 'adverb + adjective' and 'adverb + verb' sentiment scores. It is same like to the previous scheme in its method of joining the adverbs with adjectives or verbs, difference is in the logic that it counts both adjectives and verbs for choosing the overall sentiment score. We have tried it with different aggregation of weights for adjective and verb scores and conclude that 30% weight for verb score produces best precision levels. The occurrence of word 'not' has been handled in a same manner as in previous scheme. The indicative pseudo code of key step for this scheme, i.e. Senti-WordNet (AAAVC) is illustrated below. Here AAAVC refers to Adverb + Adjective and Adverb + Verb Combine.

For each sentence, extract adv+adj and adv+verb combines.
1. For each extracted adv+adj combine do:
- ❖ If adj score=0, ignore it.
- ❖ If adv is affirmative, then
  - ➢ If score(adj)>0
    - ♦ f(adv,adj)=min(1,score(adj)+sf*score(adv))

- If score(adj)<0
  - f(adv,adj)= min(1,score(adj)- sf*score(adv))
- If adv is negative, then
  - If score(adj)>0
    - f(adv,adj)= max(-1,score(adj)+sf*score(adv))
  - If score(adj)<0
    - f(adv,adj)= max(-1,score(adj)-sf*score(adv))

2. For each extracted adv+verb combine do:

- If verb score=0, ignore it.
- If adv is affirmative, then
  - If score(verb)>0
    - f(adv,verb)=min(1,score(verb)+sf*score(adv))
  - If score(verb)<0
    - f(adv,verb)=min(1,score(verb)-sf*score(adv)
- If adv is negative, then
  - If score(verb)>0
    - f(adv,verb)= max(-1,score(verb)+sf*score(adv))
  - If score(verb)<0
    - f(adv,verb)= max(-1,score(verb)-sf*score(adv))

3. fAAAVC(sentence)=f(adv,adj)+0.3*f(adv,verb)

In this scheme, we compute sentiment score for all 'adverb+adjective' and 'adverb+verb' combines in a sentence and aggregate them together. This is done for all sentences and the document-level sentiment polarity value is determined based on the aggregated sentiment score of the review document.

4.2 Aspect-level Sentiment Analysis

The document level sentiment classification is a reasonable measure of +vty or -vty expressed in a review. However in selected domains it may be a good idea to explore the sentiment of the reviewer about various aspects of items in that domain, expressed in that review. Moreover practically most of the reviews have mixture of +ve and -ve sentiment about different aspects of the items and it may be difficult and inappropriate to insist on an overall document level sentiment polarity expressed in review for the item. Thus the document level sentiment classification is not a complete, suitable and comprehensive measure for detailed analysis of +ve and -ve aspects of the items under the review. The aspect level sentiment analysis allows us to analyze the +ve and -ve aspects of an item. However, this kind of analysis is often domain specific. The aspect level sentiment analysis involves the following: a) identifying which aspects are to be analyzed , b) locating the opinionated content about that aspect in review, and c) determins the sentiment polarity of views expressed about the aspect.

Since we are restricted to phone reviews, a focused domain, we tried to explore the aspect-level sentiment analysis of the phone reviews. The first step was to identify which aspects are worth considering in phone domain. We made an extensive search for identify the aspects in different mobile phone review websites and phone magazines and worked out a list of aspects. Since a particular aspect is expressed by different-different words (such as phone screen size, its looks, pricing) by users, we created an aspect vector for all aspects under consideration. Another example is use of words like camera, audio, volume while referring to multimedia component of phone. After creating aspect vectors, we parse a review sentence by sentence. For each sentence, we look for presence of opinion about the aspect. If there is one, we use the Senti-WordNet based approach to find its sentiment polarity. This is done for all the sentences in a review and subsequently for all reviews of a phone. The scores for a particular aspect from all the reviews of a phone are aggregated to obtain an opinionated analysis of that aspect.

The sentiment analysis around aspects thus first locates an opinionated content about an aspect in a review and then uses the SentiWordNet based approach to compute its sentiment polarity. We used the SentiWordNet (AAC) scheme for this purpose. When an aspect indicating term (those terms that belong to the aspect vector created in the beginning) is located, we first lookup up to 5-gram backward for occurrence of adjectives or adverb+adjective combines. If no such term is found, we search up to 5-gram forward for their occurrence. In both cases the lookup terminates at 5-gram or sentence boundary whichever is encountered first. Then the sentiment polarity for these terms is computed using the SentiWordNet based formulation for AAC, described earlier.

Chapter 5

APPROACH

In this section we quickly describe all the procedures and objectives of this work and we aim to succeed as a result. This work sorted into 3 stages. First phase is the web page crawling phase, in which we collect the data from mobile phone review websites. The 2nd stage is the dissecting phase, in which we parse the data, prepared and dissected to find valuable information. The 3rd stage is the visualization phase, in which information is visualized to clearly understand the results.

5.1 Problem Defilation

Web blog are full of un-index and unstructured text that reflects the opinions of people. Many people make choices by taking the suggestions of other people into account. Thus, there is a need to crawl and process peoples' opinions, so that it can be used in decision making processes of potential Web review applications.

In this study, we propose a blog mining system that will extract phone comments from Web blogs and that will show Web blog users what other people think about a particular phone. Fig. shows the overall process model.

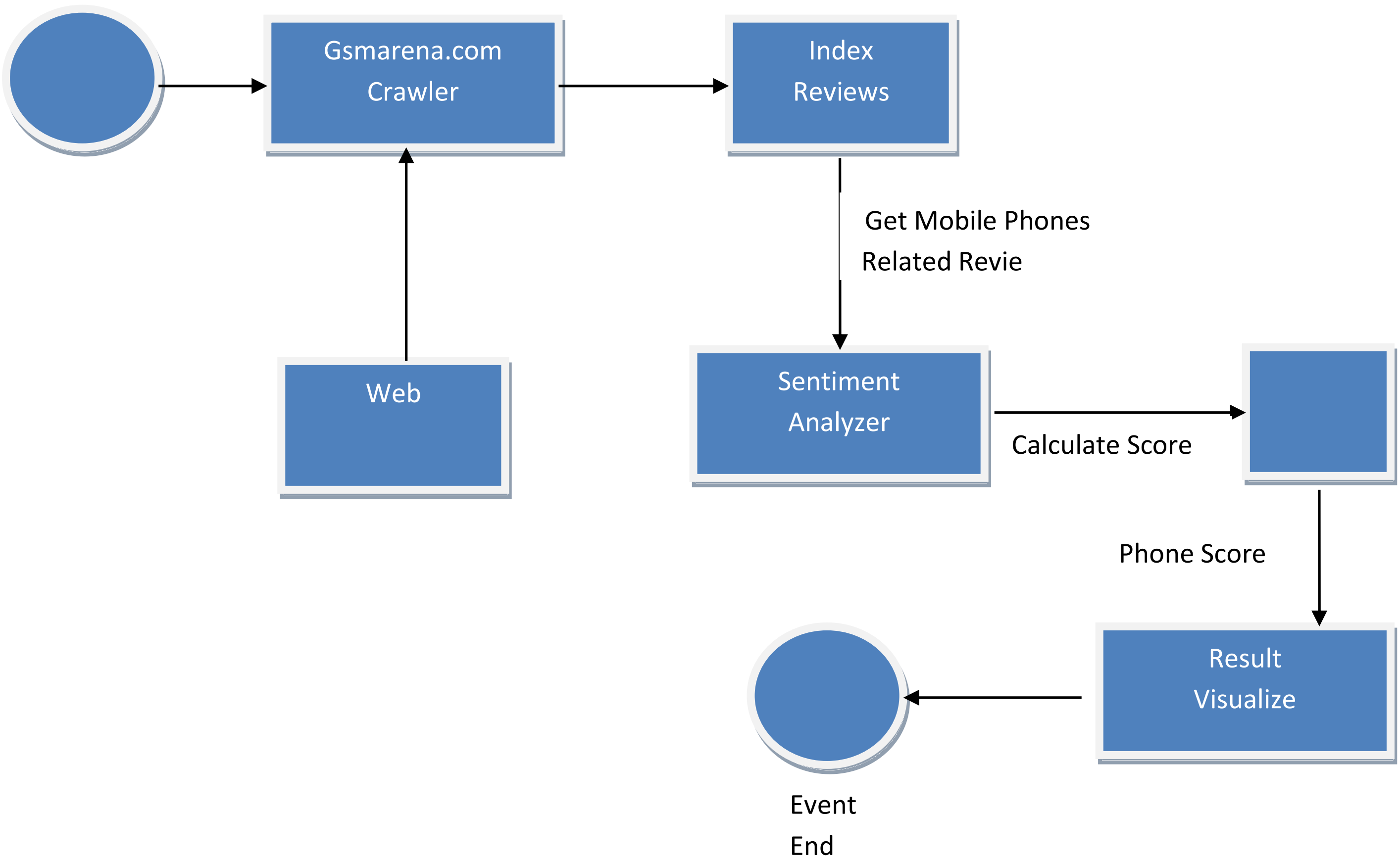

Figure 1 Overall process Model

This system architecture provides consist of several components like: Web crawler, sentiment analysis and web user interface.

5.2 Gsmarena.com Crawler

Web crawlers are the computer program that traverses the Websites in a systematic way with the purpose of collecting of data. A web crawler is use to download the Web pages for indexing and other purposes like structural analysis, page validation, visualization, update notification, for the spam purpose like collecting email addresses etc. the main objective of search engine is to provide more relevant results in faster time over rapidly expanding websites. There are 3 important sequential tasks a standard search engine does as shown[10]:

a) Crawler
b) Indexing
c) Searching

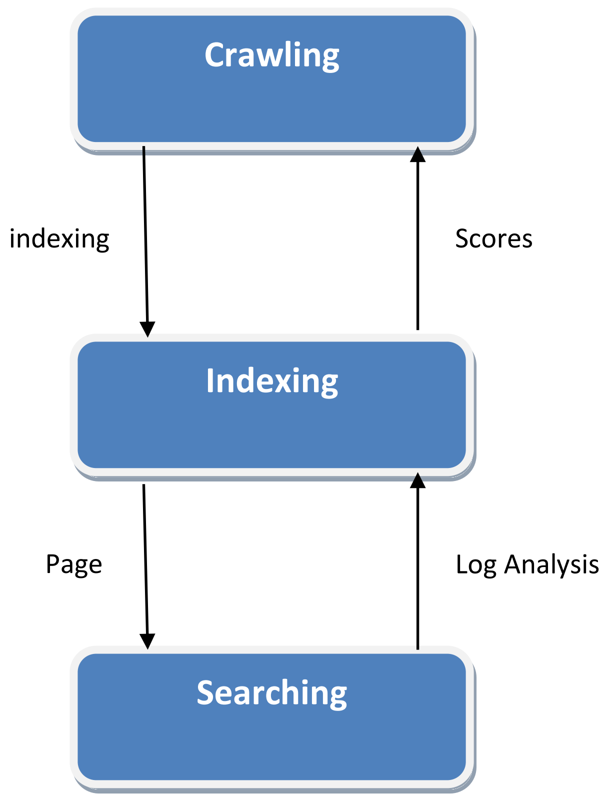

Figure 2 General sequencing task of search engine

5.3 Sentiment Analysis

'Sentiment Analysis is the task of identifying +ve and -ve opinions, emotions, and evaluations'. Sentiment Analysis has many different names. It's often referred to as Opinion mining, subjectivity analysis, and appraisal extraction with some connections in an affective computing. It is a technique for fetching opinions from unstructured human authored documents. In a simple word it is used to track the mood of public. It is an evolving field having roots in Natural Language Processing(NLP), Computational Linguistics and Textual Mining. There is a wide range of tools in the market that performs the automatic sentiment analysis of a given text. Many sentiment search engines exist in which users run typical queries on any of the topic of interest, and generate the text results. Usually results are coded and categorized into 2 or three polar categories. Some examples currently available are: Topsey, subjectivity analysis, BackTweets, Tweet Beep, Reachli, Twitterfall, Social Mention, Trackur, Sentiment.ly, Sentiment140, Twendz, Opinion Crawl, Amplified Analytics, Lithium, Open Amplify, SAS Sentiment Analysis Manager, IBM Social Sentiment Index, Twittratr, SAS Sentiment Analysis Studio, Tweet Sentiments etc.

5.4 Web User Interface

The Web user interface is formed mainly under 2 categories. The 1st category is the selection. There are two types of options in selection. 1st is the selection of phones. In Which, the system lets the user to select a phone and then shows its sentiment score results corresponding to nine different keywords categories. 2nd is the selection of keywords categories. Here, the system lets the user specify only 1 category and shows the sentiment scores on different phones under the selected keyword category.

Chapter 6

DATASET AND PERFORMANCE MEASURES

We have performed our experimental evaluation on a moderate sized dataset collected on our own. In order to evaluate the performance of our algorithmic formulations, we have computed standard Information retrieval performance measures, described ahead.

6.1 Collecting Datasets

We have collected 200 reviews each for 200 mobile phones from the popular mobile phone review database website www.gsmarena.com[15].We have labeled all these reviews manually to evaluate performance of implemented algorithmic formulations. Out of 50000 phone reviews collected, 32000 are labeled positive and 18000 are labeled as negative reviews.

6.2 Performance Evaluation

Keeping in mind the end goal to assess the exactness and execution of our algorithmic definitions, we processed the standard execution measurements of Accuracy, Precision, Recall and Fmeasure. The measure of Accuracy An utilized by us is:

$$A = \frac{Number\ of\ Correctly\ Classified\ Documents}{Total\ Number\ of\ Documents} \quad (1)$$

The equation for F-Measure Fused by us is as following:

$$Precision\ (l,c) = n_{lc}/n_c \quad (2)$$

$$Recall\ (l,c) = n_{lc}/n_l \quad (3)$$

$$F(l,c) = \frac{2*Recall(l,c)*Precision(l,c)}{Precision(l,c)+Recall(l,c)} \quad (4)$$

$$Overall\ F = \sum_i \frac{n_i}{n} \max\left(F(i,c)\right) \quad (5)$$

where Nlc is a number of documents with original label l in the classified label c, c is thenumber of documents classified as c and nl is the number of documents in original class with label l. The equation for Entropy E used by us is following:

$$E_c = -\sum_l P(l,c) * \log\left(P(l,c)\right) \quad (6)$$

$$Overall\ E = \sum_c \frac{n_c * E_c}{n} \quad (7)$$

where, P(l,c) is probability of documents of characterized class with name c belongs to original class with name l, and n is aggregate number of documents. As we can see from the comparisons above, exactness is measured in rate, though Precision, Recall and F-measure metric qualities range from 0 – 1. A littler worth for entropy metric is a marker of good execution of the calculation. We have additionally assessed slant aftereffects of our information utilizing the Alchemy API [16], to analyze the execution of our calculation.

6.3 Results

We have explored diverse linguistic highlight selection, weighing and total schemes. For document-level sentiment characterization, we used the SWN (AAC) and SWN (AAAVC) plans. We calculated result of document level sentiment classification of the info collected using both these plans and also using Alchemy API. Table I intorduces the values of performance measurements obtained for our own execution formulaes and Alchemy API.

Method	Performance measure	Value
SWN (AAC)	Accuracy	77.6%
	F-measure	0.7642532
	Entropy	0.21800485
SWN (AAAVC)	Accuracy	78.7%
	F-measure	0.77374506
	Entropy	0.21472746
Alchemy API	Accuracy	77.4%
	F-measure	0.7778397
	Entropy	0.2068102

Table 3 PERFORMANCE VALUES ON MOBILE REVIEW DATASET

The table 1 introduces an examination of the conclusion name assignments by our algorithmic plans and the Alchemy API with physically marked information. We can see that out of aggregate number of 32000 real positive reviews, SWN (AAC) marks 29000 as positive, SWN (AAAVC) names 31500 and Alchemy API marks 33521 as positive. Additionally out of 18000 real negative reviews, the three algorithmic details name negative 17600, 16760 and 18000 reviews, separately. The table III presents the rate insightful notion mark task measurements by the three algorithmic plans. As should be obvious from the table, out of 50000 aggregate reviews, the SWN (AAC) marks 82% as positive, SWN (AAAVC) names 82.9% as positive and Alchemy API names 73.4% as positive. So also out of aggregate 50000 reviews, the three algorithmic definitions name negative 18%, 17.1% and 26.6% reviews, individually.

Method	*Actual*		*Observed (in comparison to Actual)*	
		Number		*Number*
SWN (AAC)	Positive	760	Positive	678
	Negative	240	Negative	98
SWN (AAAVC)	Positive	760	Positive	688
	Negative	240	Negative	99
Alchemy API	Positive	760	Positive	634
	Negative	240	Negative	140

Table 4 COMPARISON OF SENTIWORDNET SCHEMES AND ALCHEMY API WITH MANUALLY DECIDED SENTIMENT LABELS

Method	*Phone Review Dataset*	
SWN (AAC)	POS	82%
	NEG	18%
SWN (AAAVC)	POS	82.9%
	NEG	17.1%
Alchemy API	POS	73.4%
	NEG	26.6%

Table 5 TOTAL PERCENTAGE OF '+ve' AND '-ve' LABELS ASSIGNED BY THREE METHODS

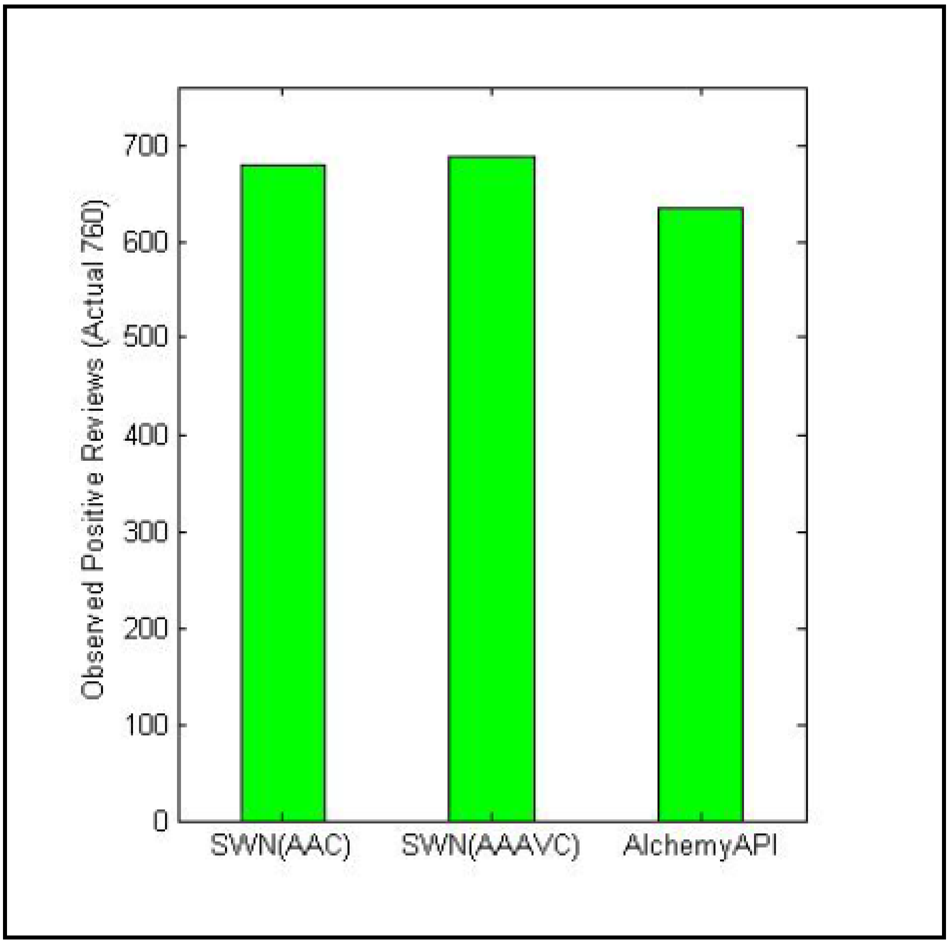

Figure 3 Correctly Classified Positive Reviews by the three methods

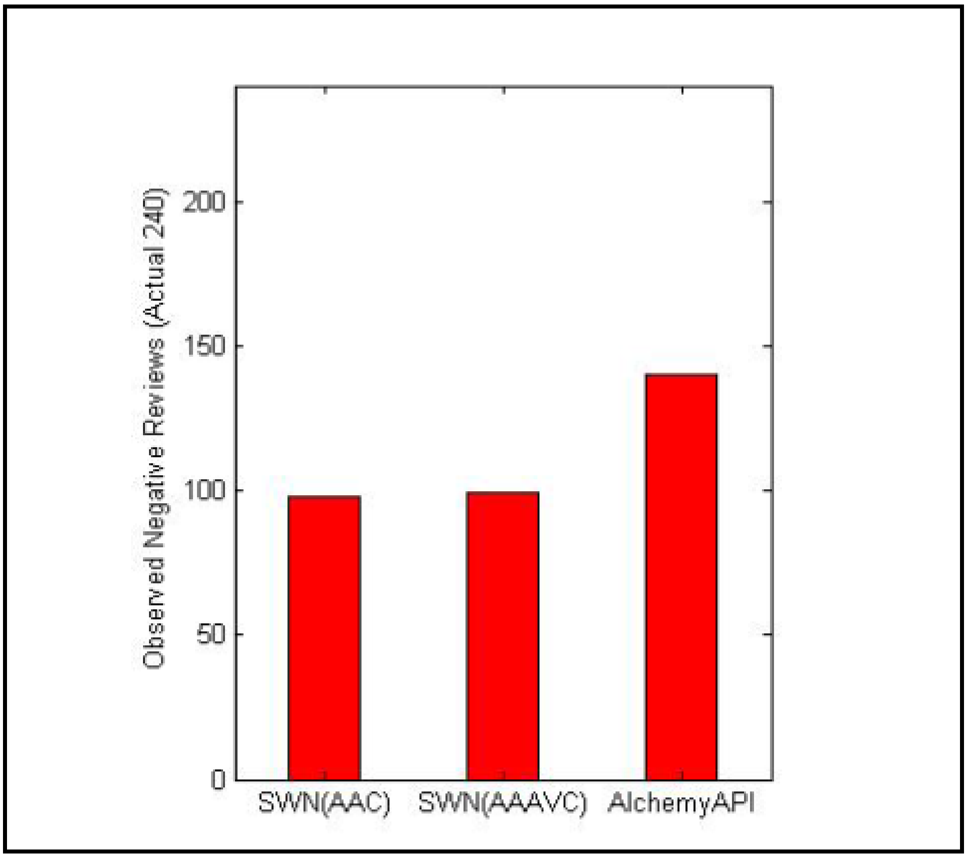

Figure 4 Correctly classified negative reviews by the three methods

As mentioned earlier, we have explored utilizing different weightage variables for adding the 'adverb+verb' sentiment scores to 'adverb+adjective' sentiment scores. We attempted with distinctive values for weightage variables for 'adverb+verb' consolidate from 10% to 100%.

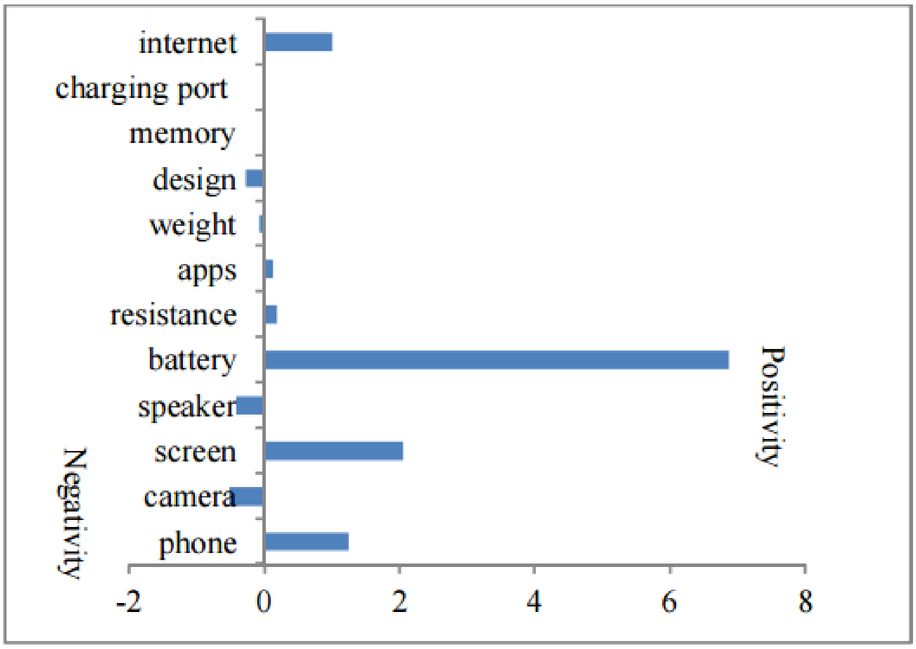

Figure 5shows the sentiment profile of Samsung Galaxy S5 with the SWN (AAC) method

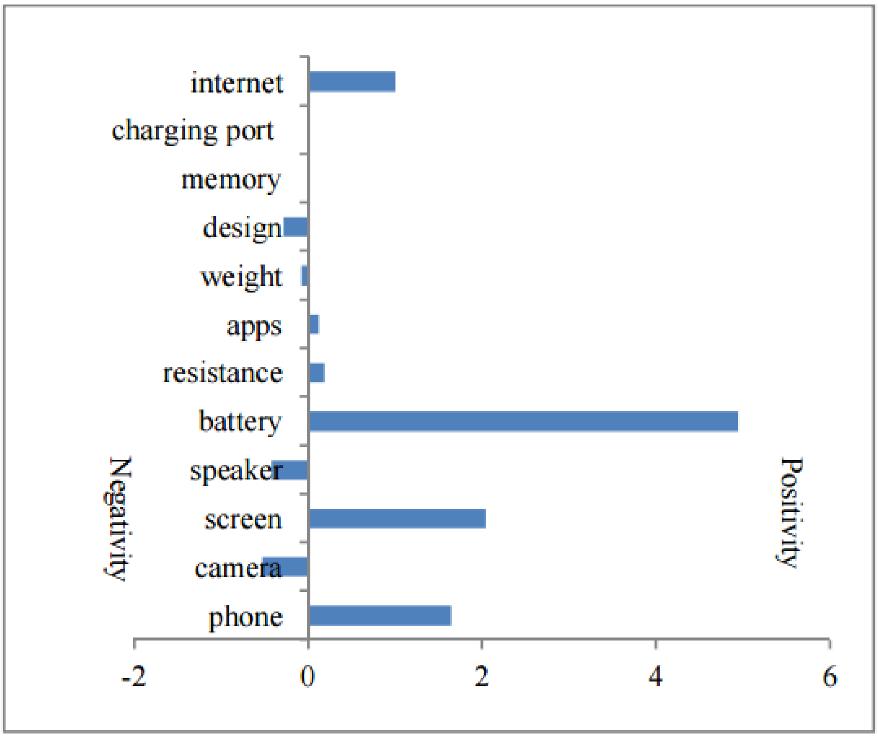

Figure 6 shows the sentiment profile of Samsung Galaxy S5 with SWN(AAAVC) method

The document-level sentiment classification results obtained by our algorithmic formual are not only accurate as compared to actual sentiment labels, but are also comparable to the results obtained by Alchemy API. Among the all three methods, SWN (AAAVC) produces the most exact results with verb score weightage factor of 30%. The SWN (AAC) strategy is closer to the performance level of SWN (AAAVC), but it's the later method which has a marginal edge

Chapter 7

CONCLUSION AND OBSERVATIONS

The document-level plans executed by us include utilization of 'Adverb+Adjective' consolidate only, and utilization of 'Adverb+Verb' combined with the 'Adverb+Adjective' combination. This is done to explore the opinionated value of distinctive linguistic features of a review and discovering a way As a result, many of the sentiment calculation were highly influenced by the tacit assumption is that a review describes about only best aggregate all the opinionated information in a review together to produce the document level sentiment summary. The results demonstrate that joining the sentiment score of 'Adverb+Verb' joins to the commonly used 'Adverb+Adjective' joined further improves the accuracy of sentiment analysis result. The best weightage factor for verb scores got through multiple experimental runs is 30%.

The aspect-level sentiment analysis algorithmic formulation designed by us is a novel and unique way of obtaining a complete sentiment profile of a phone from multiple reviews on different aspects of evaluation. The resultant sentiment profile is informative, easy to understand, and extremely useful for users. Moreover, the formulation of algorithm used for aspect level sentiment profile is very simple, easy to implement, quick in producing results and does not require any previous training. It is used on the run and produce very useful and detailed sentiment profile of a mobile phone on the different aspects of interest. This part of the implementation can be used as an addon step in the phone recommendation systems that use content filtering, collaborative filtering or hybrid approaches. The sentiment profile can also be used as an additional filtering step for designing appropriate mobile phone recommender systems as explored earlier in [18] and [19]. This aspect level sentiment profiling is a valuable form of sentiment analysis and subsequent exploitation of information expressed by a large number of users about a particular phone. The only restriction with this aspect-level implementation is that it is domain specific. However, only little changes (in aspect vectors) would be required to use this algorithmic formulation in a different domain.

Our experimental work makes two important contributions. First, it explores the use of 'Adverb + Verb' combine with 'Adverb + Adjective' combine for document level sentiment classification of a review. Second, it proposes a new feature based heuristic scheme for the aspect level sentiment classification of a phone. The aspect level sentiment classification produces an accurate and easy to understand sentiment profile of a phone on various aspects of interest. Interestingly, the aspect level sentiment profile result is congruent to the document-level sentiment classification of reviews of a phone. Though, the aspect level sentiment profile produces a more focused and accurate sentiment summary of a particular phone and is more useful for the users.

7.1 Future work

Due to the limited time to conduct this research, some of the ideas and experiments could not be evaluated while they can give us a deeper insight into sentiment classification based on text.

One of the important features of sentiment analysis is the “position feature” which means the position of sentiment words in a sentence. This feature is of a significant importance since it plays a major role in opinion classification. For instance in the sentence below, the dominant opinion is mentioned in the last word of the sentence and while the whole sentence seems negative, the polarity is positive.

“The weather in Holland is awful, the sky is always cloudy, it is always raining, but I like it”

In order to increase the accuracy of sentiment classification, it is possible to take the advantage of pattern recognition techniques such as combining classifiers. Based on this technique, we can combine several classifiers and apply them on a dataset and benefit from each classifier which outperforms in a part of the data. Ensemble can be another option as well.

Creating a large dictionary based on sentiment words and words that have a high PMI rank in sentiment classification is another trick to obtain good results for textual opinion analysis since in this model we take the advantage of dictionary based as well as corpus based constructed matrices for datasets. More informative features lead classifiers to more accurate results.

Chapter 8

SCREENSHOTS

8.1 Database structure (Tables ER)

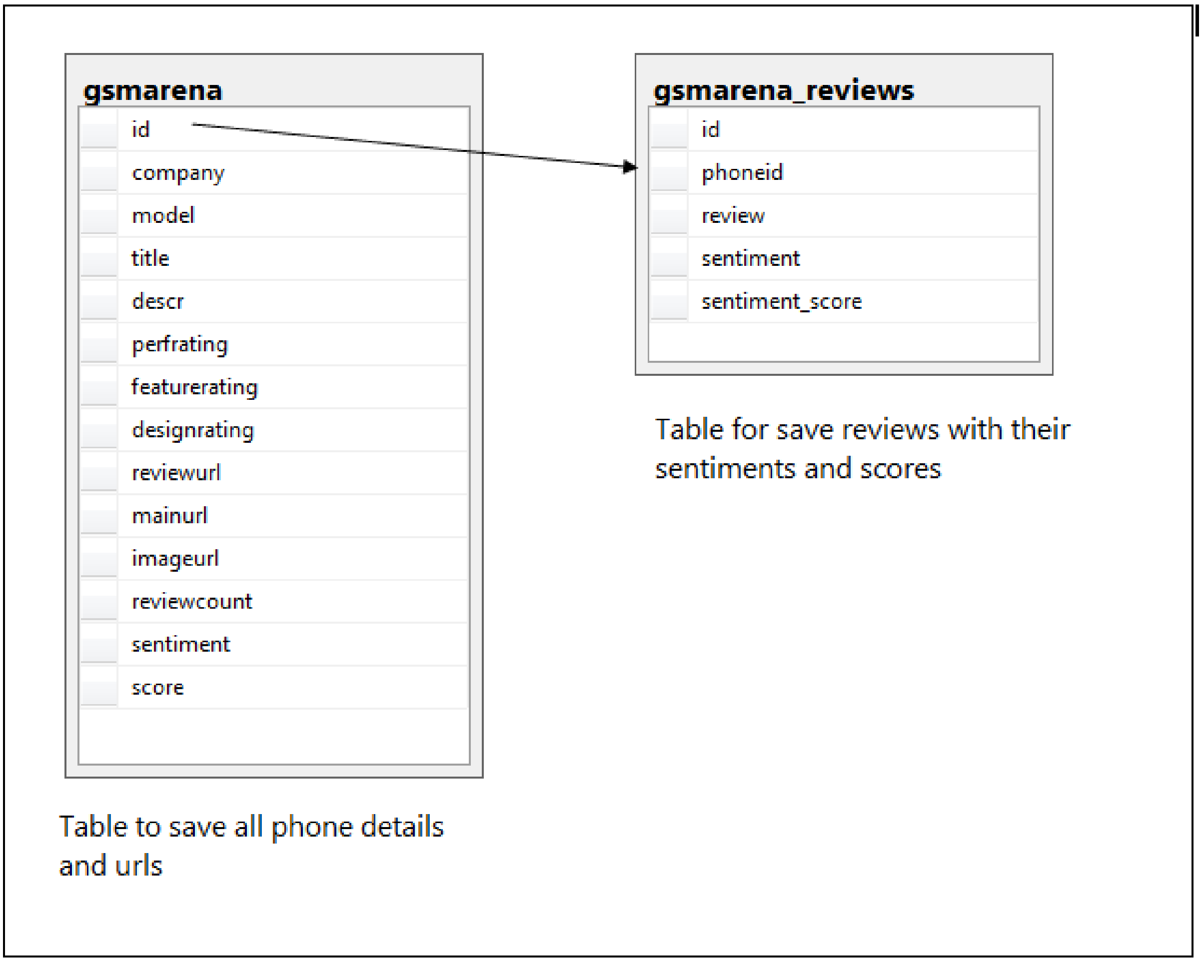

Figure 7 Database structure (Tables ER)

8.2 Website Screenshots

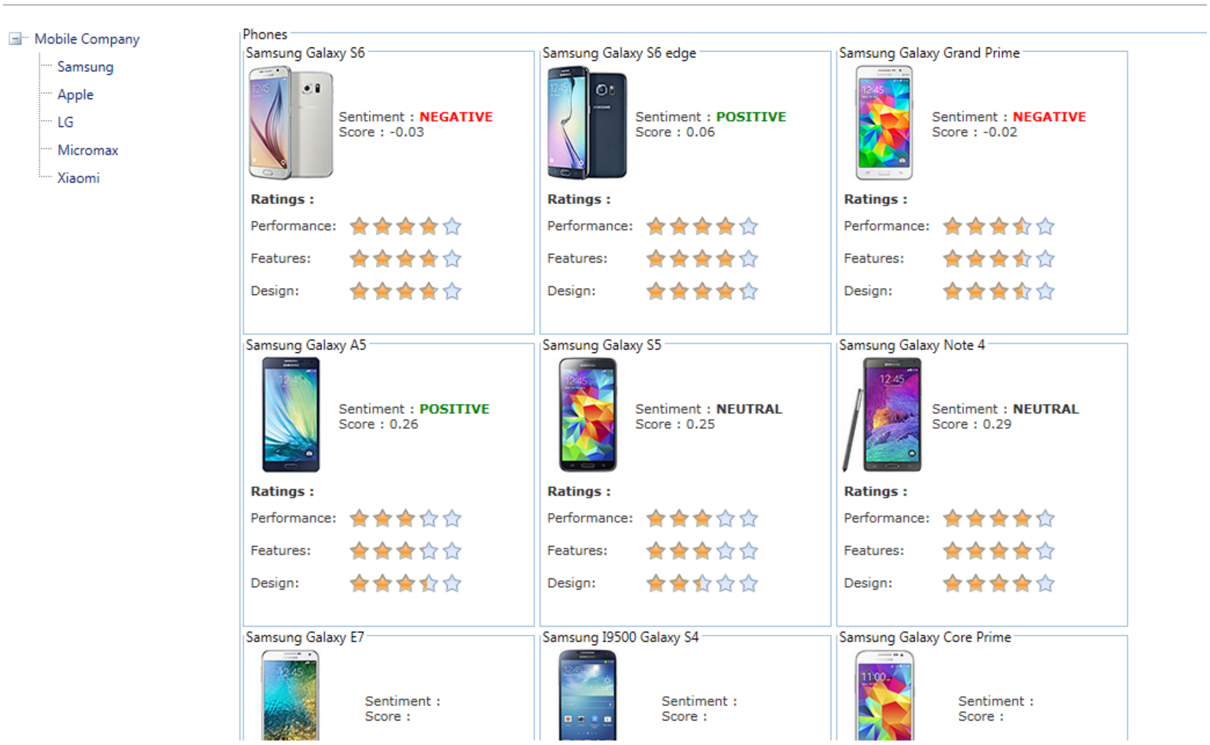

Figure 8 Website Screen1

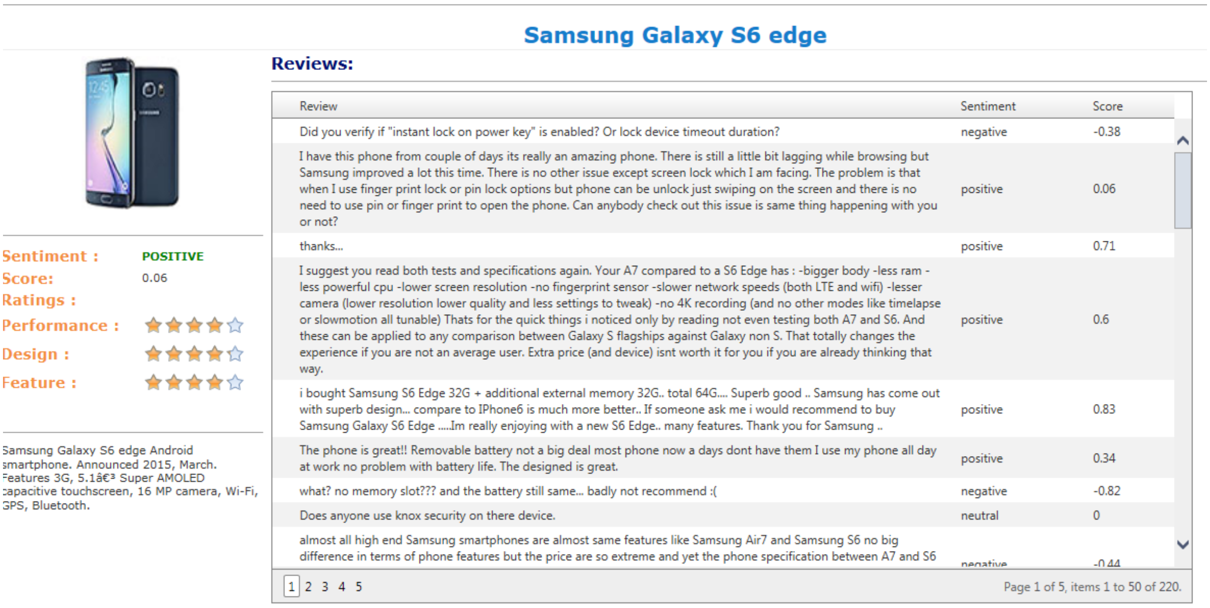

Figure 9 Website Screen 2

Publications

[1] Gaurav Dudeja, Kapil Sharma, "Sentiment Analysis of Mobile Reviews using Sentiwordnet", (Under Journal of basic and Applied Engineering Research(JBAER) Krishi Sanskriti Publications, New Delhi)

[2] Sharma, K., Dudeja, G., "Sentiment Analysis of Mobile Reviews using Sentiwordnet", (Under IEEE International Conference submission)

References

[1] M.A. Hearst, “Untangling text data mining,” Proceedings of the 37th annual meeting of the Association for Computational Linguistics on Computational Linguistics, 1999, pp. 3-10.
[2] D.J. Orre, P. Gerstl, and R. Seiffert, “Text mining: finding nuggets in mountains of textual data,” Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining, 1999, pp. 398-401.
[3] P. Falinouss, “Stock trend prediction using news articles: a text mining approach,” Lule{å} tekniska universitet, 2007.
[4] M. Sharp, “Text mining,” Rutgers University, School of Communication, Information and Library Studies, Allen, J. Natural Language Understanding, Second Edition. Redwood City, CA: Benjamin/Cummings, 2001, pp. 1-12.
[5] A. Khan, B. Baharudin, L.H. Lee, and K. Khan, “A Review of Machine Learning Algorithms for Text-Documents Classification,” Journal of Advances in Information Technology, vol. 1, 2010, pp. 4-20.
[6] A. Khan, B. Baharudin, and K. Khan, “Sentiment Classification from Online Customer Reviews Using Lexical Contextual Sentence Structure,” Communications in Computer and Information Science, Software Engineering and Computer Systems,, Springer Verlag, 2011, pp. 317-331.
[7] S. Chakrabarti, “Data mining for hypertext: A tutorial survey,” ACM SIGKDD Explorations Newsletter, vol. 1, 2000, pp. 1-11.
[8] R. Kosala and H. Blockeel, “Web mining research: A survey,” ACM SIGKDD Explorations Newsletter, vol. 2, 2000, pp. 1-15.
[9] J.M. Wiebe, “Tracking point of view in narrative,” Internation Journal of Computational Linguistics, vol. 20, 1994, pp. 233-287.

[10] J. Wiebe, T. Wilson, R. Bruce, M. Bell, and M. Martin, “Learning subjective language,” Internation Journal of Computational linguistics, vol. 30, 2004, pp. 277-308.

[11] J. Wiebe and E. Riloff, “Creating subjective and objective sentence classifiers from unannotated texts,” Computational Linguistics and Intelligent Text Processing, 2005, pp. 486-497.

[12] J.M. Wiebe, “Learning subjective adjectives from corpora,” Proceedings of the National Conference on Artificial Intelligence, 2000, pp. 735-741.

[13] B. Pang and L. Lee, “Opinion mining and sentiment analysis,” Foundations and Trends Int. J Comp Sci. Emerging Tech Vol-2 No 4 August, 2011 550 in Information Retrieval, vol. 2, 2008, pp. 1-135.

[14] B. Pang, L. Lee, and S. Vaithyanathan, “Thumbs up: sentiment classification using machine learning techniques,” Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10, 2002, pp. 79-86.

[15] S.M. Kim and E. Hovy, “Determining the sentiment of opinions,” Proceedings of the 20th international conference on Computational Linguistics, 2004, pp. 1367-1374.

[16] J.M. Wiebe, “Identifying subjective characters in narrative,” Proceedings of the 13th conference on Computational linguistics-Volume 2, 1990, pp. 401-406.

[17] A. Esuli and F. Sebastiani, “Determining term subjectivity and term orientation for opinion mining,” Proceedings the 11th Meeting of the European Chapter of the Association for Computational Linguistics (EACL-2006), 2006, pp. 193-200.

[18] S.M. Kim and E. Hovy, “Automatic detection of opinion bearing words and sentences,” Companion Volume to the Proceedings of the International Joint Conference on Natural Language Processing (IJCNLP), 2005, pp. 61-66.

[19] S. Bethard, H. Yu, A. Thornton, V. Hatzivassiloglou, and D. Jurafsky, “Automatic extraction of opinion propositions and their holders,” 2004 AAAI Spring Symposium on Exploring Attitude and Affect in Text, 2004, pp. 2224-2236.

[20] P. Turney, “Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews,” Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL’02), 2002, pp. 417-424.
[21] S. Argamon, K. Bloom, A. Esuli, and F. Sebastiani, “Automatically determining attitude type and force for sentiment analysis,” Human Language Technology. Challenges of the Information Society, 2009, pp. 218-231.
[22] L. Polanyi and A. Zaenen, “Contextual valence shifters,” Computing attitude and affect in text: Theory and applications, 2006, pp. 1-10.
[23] S. Hariharan, R. Srimathi, M. Sivasubramanian, and S. Pavithra, “Opinion mining and summarization of reviews in web forums,” Proceedings of the Third Annual ACM Bangalore Conference, 2010, pp. 1-4.
[24] C.W.K. Leung and S.C.F. Chan, “Sentiment Analysis of Product Reviews,” Encyclopedia of Data Warehousing and Mining Information Science Reference,, 2008, pp. 1794-1799.
[25] A. Andreevskaia and S. Bergler, “Mining WordNet for fuzzy sentiment: Sentiment tag extraction from WordNet glosses,” Proceedings of EACL, 2006, pp. 209-216.
[26] M. Koppel and J. Schler, “The importance of neutral examples for learning sentiment,” Computational Intelligence, vol. 22, 2006, pp. 100-109.
[27] T. Zagibalov and J. Carroll, “Unsupervised classification of sentiment and objectivity in Chinese text,” IJCNLP, 2008, pp. 304-311.
[28] B. Pang and L. Lee, “Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales,” Proceedings of the ACL, 2005, pp. 115-124.
[29] A.B. Goldberg and X. Zhu, “Seeing stars when there aren’t many stars: Graph-based semi-supervised learning for sentiment categorization,” Proceedings of the First Workshop on Graph Based Methods for Natural Language Processing, 2006, pp. 45-52.
[30] X. Zhu and A.B. Goldberg, “Kernel regression with order preferences,” PROCEEDINGS OF THE NATIONAL CONFERENCE ON ARTIFICIAL INTELLIGENCE, 2007, pp. 681-686.

[31] A. Andreevskaia and S. Bergler, “When specialists and generalists work together: Overcoming domain dependence in sentiment tagging,” Proceedings of ACL-08: HLT, 2008, pp. 290-298.
[32] C.W.K. Leung, S.C.F. Chan, and F. Chung, “Integrating collaborative filtering and sentiment analysis: A rating inference approach,” Proceedings of The ECAI 2006 Workshop on Recommender Systems, 2006, pp. 62-66.
[33] P.D. Turney, “Mining the web for lexical knowledge to improve keyphrase extraction: Learning from labeled and unlabeled data,” Int. J Comp Sci. Emerging Tech Vol-2 No 4 August, 2011 551 Journal of Artificial Intelligence Research, Arxiv preprint cs/0212011, 2002, pp. 1-34.
[34] A. Esuli and F. Sebastiani, “Determining the semantic orientation of terms through gloss classification,” Proceedings of the 14th ACM international conference on Information and knowledge management, 2005, pp. 617-624.
[35] C.O. Alm, D. Roth, and R. Sproat, “Emotions from text: machine learning for text-based emotion prediction,” Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing, 2005, pp. 579-586.
[36] T. Wilson, J. Wiebe, and P. Hoffmann, “Recognizing contextual polarity in phrase-level sentiment analysis,” Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing, 2005, pp. 347-354.
[37] http://google.com
[38] http://sentiwordnet.isti.cnr.it
[39] http://www.sentiwordnet.isti.cnr.it
[40] http://www.gsmarena.com