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Expressive Sentiment Analysis of Product Reviews Using Opinion Mining

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ABSTRACT: Now a days posting reviews on products is one of the popular way for expressing opinions and grievances toward the products brought or services received. By making Analysis of those number of reviews available would produce useful as well as actionable knowledge that could be of economic values to vendors and other interested parties. From this the problem of mining reviews for product and predicting the sales performance are tackled. Currently, there are many challenges in translating human affect into explicit representations. The current and sentiment analysis algorithms uses simple terms to express opinions about a product or particular service. But the cultural factors, traditional linguistic barriors and differing contexts make it extremely difficult to turn a string of written text into a simple pro or con sentiments. The research in the field started with sentiment and subjectivity classification, which treated the problem as a text classification problem. Sentiment classification classifies whether product reviews or sentence expresses a positive or negative opinion. Subjectivity classification determines whether a sentence is subjective or objective. Many real-life applications, however, require more detailed analysis because users often want to know the subject of opinions. The present work focuses on the categorization of a plain input text to inform a Text To Speech system about the most appropriate sentiment to automatically synthesize expressive speech at the sentence level. In addition to this reviews are also evaluated using Text To Speech System with other language and consider a temporal analysis for the evolution of conversation. Text-to-speech system converts normal language text into speech.

KEYWORDS: Review mining, Sentiment analysis, Text To Speech, polarity, opinion mining.

I. INTRODUCTION

The ever-growing amount of available information in the Social Web fosters the proliferation of business and research activities around the relatively new fields of opinion mining and sentiment analysis. The automatic analysis of user-generated content such as online news, reviews, blogs, and tweets, in fact, can be extremely valuable for tasks such as mass opinion estimation, corporate reputation measurement, political orientation categorization, stock market prediction, customer preference, and public opinion study. Communication platforms, such as blogs, wikis, online forums, and social-networking groups, have become a rich data-mining source for the detection of public opinions [3],[8],[9],[22].It has become a common practice for e-commerce websites to provide the venues and facilities for people to publish their reviews, with a prominent example being Amazon (www.amazon.com). Reviews are also prevalent in blog posts, social networking websites as well as dedicated review websites such as Epinions (www.epinions.com).A lot of conceptual rules, in fact, govern the expression of opinions and sentiments and there exist even more clues that can convey these concepts from realization to verbalization in the human mind. For instance, a company can study the public sentiment in tweets to obtain users' feedback towards its products; while a politician can adjust his/her position with respect to the sentiment change of the public. Publicly available opinions provide valuable information for decision-making processes based on a new collective intelligence paradigm referred to as crowd sourcing. This has inspired research in opinion mining and sentiment analysis to develop methods for automatically detecting emotions, opinions, and other evaluations from texts.

One of the most relevant applications of opinion mining and sentiment analysis is aspect-based summarization.[8],[17] Broadly speaking, given a collection of opinion posts, this task is aimed at obtaining relevant aspects(such as product features), along with associated sentiment information expressed by customers (usually an opinion word and/or a polarity score).Aspect-based summarization is usually composed of three main tasks: aspect

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identification, sentiment classification, and aspect rating. Aspect identification is focused on extracting the set of aspects or product features from the source collection. The word aspectis intended to represent the opinion or sentiment targets, which are also referred to as product features3 when the collection of posts—typically, customer reviews—is about products or services. For example, given the sentence, "The bed was comfortable" in a review about a hotel room, the aspect being referred to is "bed" and the opinion is positively expressed by means of the opinion word "comfortable."

The sentiment classification task consists of determining the opinions about the aspects and/or their polarities, where as aspect rating leverages the relevance of aspects and their opinions to properly present them to users.

II. RELATED WORK

A growing number of recent studies have focused on the economic values of reviews, exploring the relationship between the sales performance of products and their reviews [1], [6]. Since what the general public thinks of a product can no doubt influence how well it sells, understanding the opinions and sentiments expressed in the relevant reviews is of high importance, because collectively these reviews reflect the "wisdom of crowds"(what the general public think) and can be a very good indicator of the product's future sales performance. This work concerned with generating actionable knowledge by developing models and algorithms that can utilize information mined from reviews. Such models and algorithms can be used to effectively predict the future sales of products, which can in turn guide the actions of the stakeholders involved.

Prior studies on the predictive power of reviews have used the volume of reviews or link structures to predict the trend of product sales [1], [5], failing to consider the effect of the sentiments present in the blogs. It has been reported [1],[5] that although there seems to exist strong correlation between the volume of reviews and sales spikes, using the volume or the link structures alone do not provide satisfactory prediction performance. Indeed, as we will illustrate with an example, the sentiments expressed in the reviews are more predictive than volumes.

In addition, another important aspect that has been largely overlooked by those prior studies, is the effect of the reviews' quality on their predictive power. Quality wise, not all reviews are created equal. Especially in an online setting where anybody can post virtually anything, the quality of reviews can vary to a great extent. Examples of "bad" reviews include very short insulting comments with no substance like "This booksucks," or long and tedious reviews that are simply duplicates of the product descriptions. Reviews poorly written, reviews containing no subjective judgment, or even spam reviews, may actually negatively affect the accuracy of the prediction, if they are not properly taken care of.

Previous work on extracting product features from customer reviews has mainly relied on natural language processing (NLP).[2] Part-of-speech (POS)tagging, shallow parsing techniques, and dependency grammars have been widely applied to identify both noun phrases that act as potential features and opinion words that affect them through syntactical dependencies.

Using the double-propagation strategy[11] allows the incremental identification of features and opinion words from a predefined initial set (usually a lexicon of opinion words). Generally, NLP-based approaches present good precision but low recall figures because they depend on the definition of extraction patterns, which are dependent on both the particular language and the reviews application domain. Another limitation of NLP-based approaches is that they don't account for feature relevance. Thus, an additional process is required for scoring the identified features. Most approaches just apply simple statistics such as word counts to rank the features.

III. PROPOSED WORK

In this work, reviews of the product are found on the basis of comments of users available on internet. As reviews collected from internet would be in raw format. Few steps are taken to convert these raw date into formatted information. During this, few text files are generated at various steps of processing. Then formatted information is processed to get review of the product. Steps involved in the work is as follows

1) User is asked to enter product name.

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2) Software then searches product reviews from internet and stored in one text file. As mentioned earlier, collected text is in raw format. Following steps are taken to convert collected data into required format.
   - As reviews are collected from web pages, these collected reviews contain various html tags. So first step is to remove these tags from the reviews. New text file is created and text without tags is stored in this file.
   - Now, text is in the form of various paragraphs. In this step, all the paragraphs are splitted into sentences and text is stored sentence wise in new text file.
   - After this, text generated in the previous step is undergone POS tagging procedure which tags every part of speech of each sentence. Output of this step is stored in new text file.
3) Now, as formatted information is available, this information is processed to get review of product. To get review, process mainly focused on adjective, adverb and connectors.
4) Adjectives and adverbs are classified into three classes-Positive, Negative and Neutral. These classes are stored as Wordnet. Depending upon these classes, polarity is given to each tagged sentence. Then percentage of sentences having positive polarity is found out. This value is used to find whether product is excellent, good, average or bad.
5) Again If percentage obtained in previous step is also divided in four classes and those are as follows

Sr. No.	Percentage	Review
1	0 to 30	Bad
2	31 to 55	Average
3	56 to 80	Good
4	81 to 100	Excellent

Table 1: Categorization of Product

6) This review is then given to user not only in textual format but also in voice format too.

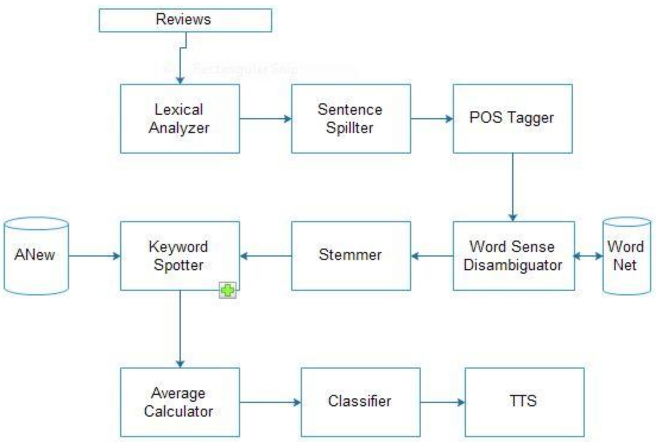

Figure 1: Proposed System Diagram

1. Reviews Collection

The reviews are collected from the Google and stored in text format.

2. Polarity Identification

In this step the review is taken as an input. The inputted review is considered one by one for the polarity identification step. The purpose of this step is to filter all the unrequired words that are neither related to sentiment analysis nor feature analysis. Here, the positive and negative words from the considered reviews are identified. The identification step is considering the reviews and with the help of sentence splitter, splitting the review one by one as an input.

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3. Polarity Comparison

The above identification output provides us with the important polarity and the feature words only. Now in this step the above output polarity and feature words are compared with the help of rule based approach. The rule based approach deals with the designing of the rules by observing the review data. Generally the four rules have been defined by observing the common pattern in the reviews. The rule based approach works with comparing the identified word with the defined datasets with the help of word matching process. In this process the identified words are matched with the dataset and only complete word matching are allowed for the purpose of comparison. The words with short cuts and wrong spell are not considered for the performance of the system.

4. Dataset

For the above comparison purpose we required some datasets that will help in classifying the polarity in terms of positive and negative and classifying only related features of the app. The proposed system consists of 4 dataset they are as follows:

Positive Dataset: This dataset is created for comparing all the positive words.

Negative Dataset: This dataset is created for comparing all the negative words.

Neutral Dataset: This dataset is created for comparing all the neutral words.

5. Word Net

The Dictionary consist of all the positive and negative words as per our knowledge mark with the tag words then this tag words are searched in the above datasets(positive / negative)for comparing the polarity of the words.

6. Polarity Result

The polarity results provides us with the positive, negative and neutral counts of the words present in the inputted reviews. The rules efficiency are tested by finding out the polarity words manually and comparing both the results a near to some value is obtained.

7. Total Result

The total result is obtained from the polarity result and classification is done in five different categorize to get the result for the user as well as developer. The result facilited user to correctly judge which product to be used and which to not. The developer by seeing the result are in a state what the problem is exactly in the system and which features should be improved.

IV. EXPERIMENTAL RESULT ANALYSIS

The results of the opinion mining are computed by using the parameters precision and recall. Precision and recall are the basic measures used in evaluating search strategies.

Precision is one measure of the effectiveness of some computer applications for finding search words, candidate terms, and other items. Precision is a measure of the proportion of the results of a computer application that are considered to be pertinent or correct.

Recall is one measure of the effectiveness of some computer applications for finding search words, candidate terms, and other items. Recall is a measure of the proportion of all possible correct results of a computer application that the application actually produces. For example, suppose you are using a computer application to search for terms in a document that has 100 terms in it. You know because you counted them. If the application finds 80 of these terms, then the recall of the application is 80 out of 100, or 80% .In this system these two parameters are evaluated for checking the accuracy of the system.

The rule based approach of the system is tested with reviews of the three products and the following results are calculated for simplification the results are manually checked with the minor changes. Table 1 represents the results of review calculation for three products.

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Table 2: Reviews calculation

Sr No	Product Name	Positve Word	Negative Word	Neutral Word	Positive Review %
1	Acer Laptop	146	46	159	76%
2	Samsung Mobiles	150	39	138	79%
3	Dell Laptop	123	54	159	73%

System is used to find review for one of the product. It is found that system collected 119 opinions from internet. These opinions are undergone procedure explained in previous section. System found that out of 119 opinions, 59 were positive, 41 neutral and 19 negative opinions. To calculate percentage of positive opinions, following formula is user

$$\text{Positive reviews} = \frac{\text{Number of positive opinions}}{\text{Number of positive opinions} + \text{number of negative opinions}} * 100$$

Therefore, percentage of positive opinions according to system is equal to

$$\frac{59}{59+19} * 100 = \frac{59}{78} * 100 = 75.64\%$$

To analyze result of the proposed system, same set of opinions are manually analyzed and found that out of 119 opinions, 79 were positive, 29 neutral and 11 negative opinions.
Therefore, percentage of positive opinions according to manual calculation is equal to

$$\frac{79}{79+11} * 100 = \frac{79}{90} * 100 = 87.77\%$$

So, from above calculations, it is found that there is error of 12.13. So error percentage equal to

$$\frac{12.13}{87.77} * 100 = 13.82\ \%.$$

Hence, correctness percentage of system's review is equal to 100-13.82=86.18%.
Here the table shown below will provide us with the number of adjectives and adverbs found for the product by the system and also the number of adjectives and adverbs which were not found, it is counted by us. The Table shows recall value calculated for adjective and adverbs.

Table 3: Recall calculation

Sr. No.	**Product**	**No. of Adjective Found**	**No. of Adjective Not found**	**Recall (adjective)**	**No. of Adverb Found**	**No. Adverb Not Found**	**Recall (Adverb)**	**Average Recall**
1	Acer Laptop	72	44	62%	68	45	60%	61%
2	Samsung Mobile	84	48	64%	78	38	67%	65.5%
3	Dell Laptop	98	37	73%	69	48	59%	66%
Overall Average Recall								64%

The precision ratio of the correct reviews and the total reviews are calculated and shown in the table no.3. The graph represents the precision value of the three product.

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Table 4: Polarity precision calculation

Sr. No.	Product	Correct Review	Total Review	Precision
1	Acer Laptop	261	351	74%
2	Samsung Mobile	196	281	69%
3	Dell Laptop	259	340	76%
Overall Average Precision				73%

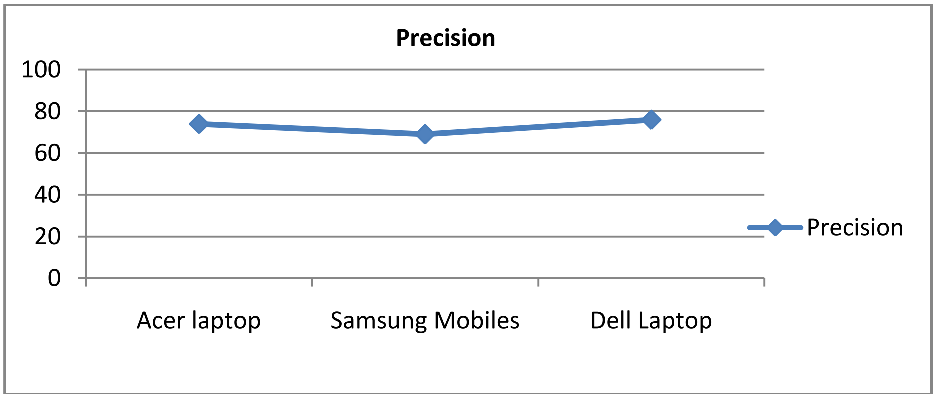

Figure 2: Precision Graph

.The figure provides us with the precision graph.

Table 5: Results of Existing system

Sr no	App Name	Correct Word	Incorrect Word	Precision
1	Angry Birds	290	45	78%
2	Whatsapp	250	50	73.33%
3	Toi	265	55	68 %

Table 6.: Results of Proposed system

Sr no	App name	Correct reviews	Incorrect review	Precision
1	Acer Laptop	330	36	84%
2	Samsung Mobile	275	42	85%
3	Dell Laptop	280	46	79%

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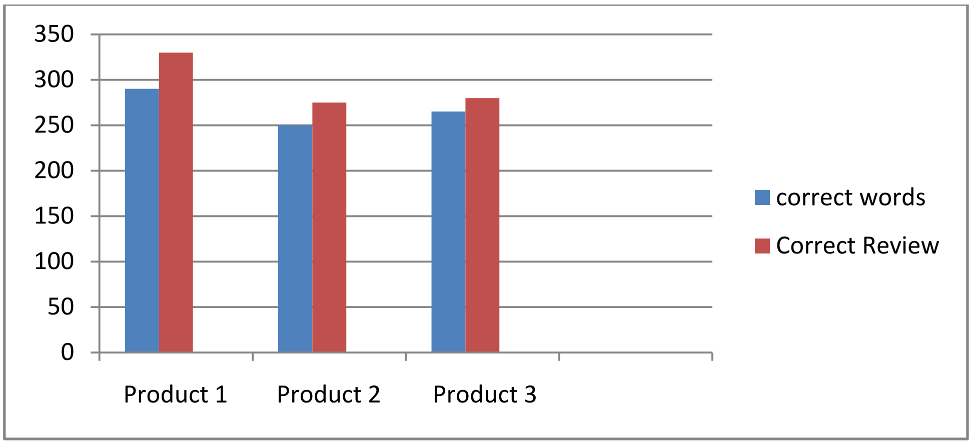

Figure 3: Comparision of Correct Words Versus Correct Reviews

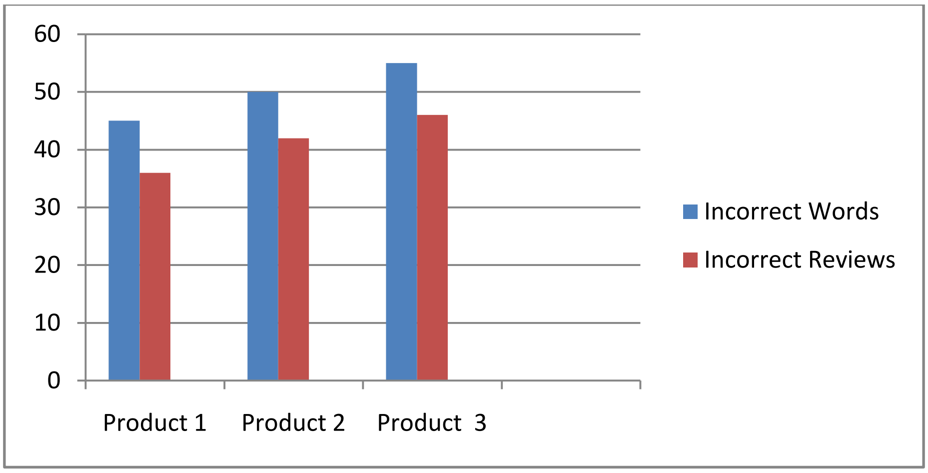

Figure 4: Comparision of Incorrect Words Versus Incorrect Reviews

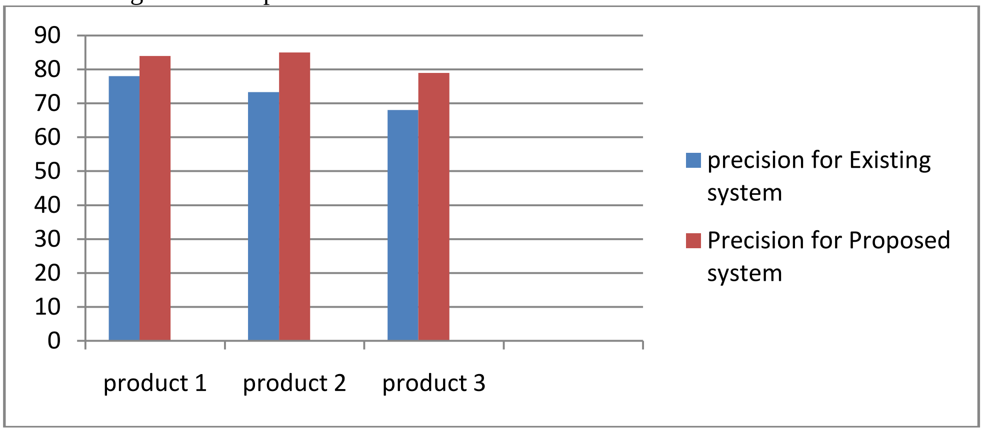

Figure 5: Comparision of Precision Values of Existing System Versus Proposed System

Thus the results are calculated and we get the actual performance of the system.

V. CONCLUSIONS AND FUTURE SCOPE

Sentiment Analysis is a Natural language processing and information extraction task that aims to obtain writer's feelings expressed in positive or negative comments, questions and requests, by analyzing a large number of

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documents. In this work, user is asked to enter name of product. After that system gathers news and reviews related to product from the internet. Information gathered from the internet is formatted in various steps such as removal of HTML tags, Lexical analysis, POS tagging , etc. Formatted information is then undergone process to find out number of positive, negative, neutral reviews. Depending on percentage of positive reviews, product final review is divided into 6 categories. Not only final review is displayed to the user but also system speaks final review of product.

The system can be further modified and certain objectives can also be achieved for these system. In future, firstly more rules can be applied on the tagged files so that system will give more précised review. And more focus will be given to noun which will be enable us to find who has commented for particular product. Future efforts will concentrate on expanding the basic premise underlying latent affective analysis into a more general framework which supports different mapping instantiations and integrating the new framework into the text analysis component of our TTS system. In order to achieve affective congruence, it is necessary to properly translate any emotion detected into appropriate prosodic effects.

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