



Sentiment Mining on Products Features based on Part of Speech Tagging Approach

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Abstract

In today's competitive business, paying attention to the feedback from customers has become a valuable factor for organizations. Organizations have found that satisfied customers are not only a repeated buyer, they are also propaganda arm of the organization. Therefore, the correct analysis of their feedback by relying on information technology tools is a key element in the success of the organizations in trade. People generally share their opinions about purchased goods on the Web sites or in social networks. Extraction of these opinions is known as a special branch of text mining under the term of sentiment mining. Although this category is brand new, but in recent years, extensive researches have been done on sentiment analysis and classification of intentions. Therefore, in this paper a model is suggested about sentiment mining with the ability to extract users' opinion and product features. So dataset of customer comments has been made in a way that the comments are taken from a Website about some specific digital products. Then the paragraphed opinions are converted into sentences and the sentences are separated into two categories of subjective and objective. Next, user's opinion and product features are taken from subjective sentences by using StanfordPOSTagger and relying on Tf-idf factor for product features and finding opinion polarity by using SentiWordNet tools. In this way, user satisfaction of specific features of the product can be detected. As a means of evaluation, three factors of Recall, Precision and F-Measure provide an indication of the accuracy of each part of this research.

Keywords: Opinion mining, Sentiment mining, Subjective and objective sentences, Text mining.

I. Introduction

Surveys about public social events, political movements, trade strategies, marketing and product advantages, appear as a challenging subject. Traditional methods required to ask a large numbers of people about their feelings on the census by online or offline networks. By changing the direction of using the web, like information production and information sharing (Web 2.0), social media services have emerged. Now online users can easily express their opinions through news portals, discussion forums, publications, messages, blogs and micro-blogs or tweets. So the consent of the people to engage in social interactions dramatically has been increased. By using opinion mining and sentiment analysis of users who shared their feedback in social networks, we can achieve the desired results.



(Jafari and Minayi, 2012) proposed a method for analyzing the reviews in Farsi language. In this research, user comments were proposed on a feature level in the e-shop and the algorithm presented in English was improved to Persian by identifying subjective sentences on the text. Then the evaluation by web scraping and Mozenda software shown an improvement of 27% is achieved.

In the research by (Montejo-Ráez et al., 2013), the proposed method combines SentiWordNet scores with a random walk analysis of the concepts found in the text over the WordNet graph. The approach is compared with simple scoring of sentences based on the values assigned to individual concepts in SentiWordNet and also with supervised learning using Support Vector Machines. They show that such an unsupervised approach can obtain similar results to SVM, without requiring annotated training corpora and being applicable to any domain.

In order to extract positive feeling of customers for 16 world brands (Mohamed, 2013) used sentiment analysis for customers brands on Twitter by counting the number of words of English with relative frequency. For coding textual data posted on Twitter, QDAMiner 4.0 software package was used. And then twitter and the ggplot2 libraries in the R software package version 2.15 to conduct the quantitative sentiment score were used. Finally, they used the StreamGraph software package to visualize the trend of tweets across a period of time for all brands (Clark, 2008).

In the study by (Liu and Hu, 2004 'a'), sentiment statements were analyzed on a sentence level which first downloads all the reviews and stores them in the database. After that a POS tagger tags all the reviews which will work as hooks for the mining part responsible for finding frequent features. This step is skipped by some systems which employs manual feature annotation as in the study by (Li and Zhao, 2009) where ontologies were used to annotate movies features manually. Next, with the tagged sentences and features identified, opinion words are extracted and their semantic orientation is identified with the help of WordNet. Now with opinion words identified and extracted, the system identifies infrequent features. In the last part of the process the orientation of each sentence is identified, and a summary is generated. This method works well but it hides a very important detail which in the article by (Yu et al., 2008) this problem is solved, through sentiment analysis in the feature.

(Fu et al., 2013), have worked on text-based affect analysis (AA) of Japanese narratives from Aozora Bunko. In their research, they addressed the problem of person/character related affect recognition in narratives. They extracted emotion subject from a sentence based on analysis of anaphoric expressions at first, then the affect analysis procedure estimated what kind of emotional state each character was in for each part of the narrative.

(Xia et al., 2011) made a comparative study of the effectiveness of ensemble techniques for sentiment classification. Three types of ensemble methods of feature sets and classification algorithms were evaluated on reviews of movies and products. In another early work, (Turney, 2002) applied an unsupervised learning algorithm to classify the emotional orientation of users' reviews (i.e., reviews of movies, travel destinations, automobiles and banks). His approach calculated the mutual information between each phrase and the word "excellent", as well as the mutual information with the word "poor". Then, the difference of the two mutual information scores was used to classify each review as "recommended" or not.

Affect emotion words could be used as presented by (Keshtkar and Inkpen, 2012) using a corpus-based technique. In this work, a bootstrapping algorithm is introduced based on contextual and lexical features for identifying paraphrases and to extract them for emotion terms,



from nonparallel corpora. They started with a small number of seeds (WordNet Affect emotion words). This approach learned extraction patterns for six classes of emotions.

In the study by (Pak and Paroubek, 2010) also a corpus of tweets for sentiment analysis was generated, by selecting positive and negative tweets based on the presence of specific emoticons. Subsequently, they compare different supervised approaches with n-gram features and obtain the best results using Naïve Bayes with unigrams and part-of-speech tags.

ED on a sentence level was proposed by (Lu et al., 2010) .They proposed a web-based text mining approach for detecting emotion of an individual event embedded in English sentences. This approach was based on the probability distribution of common mutual actions between the subject and the object of an event. Web-based text mining and semantic role labeling techniques were integrated, together with a number of reference entity pairs and hand-crafted emotion generation rules to recognize an event emotion detection system. They did not use any large-scale lexical sources or knowledge base. It was shown that this approach revealed a satisfactory result for detecting the positive, negative and neutral emotions. It was proved that the emotion sensing problem is context-sensitive.

II. Methods

In this paper five electronic products are selected from amazon.com. 301 users' comments were collected and saved in a database. The database columns include a number for each comment, the product name, context of comments about the specific product and a number which shows the number of comments. Then each comment which was a paragraph will be divided into separated sentences, which in figure 1 is displayed:

CommentID	product	sentimentWord	wordID
1	Canon G3	I recently purchased	1
2	Canon G3	The camera is nice	1
3	Canon G3	after I took photo	1
4	Canon G3	I just took them	1
5	Canon G3	they find away	1
6	Canon G3	a lot of my own	1
7	Canon G3	I've really enjoyed	1
8	Canon G3	more you get a	1
9	Canon G3	beautiful view	1
10	Canon G3	I've highly recommend	1
11	Canon G3	great job camera	1
12	Canon G3	wow	1
13	Canon G3	this is my first digi	1
14	Canon G3	I am a software	1
15	Canon G3	just a little more	1
16	Canon G3	whether you are	1
17	Canon G3	you can have	1
18	Canon G3	at its best	1
19	Canon G3	I am using	1
20	Canon G3	a little bit of	1
21	Canon G3		
22	Canon G3		
23	Canon G3		
24	Canon G3		
25	Canon G3		

Figure. 1. Sentence extraction from users' comments.

A. Model framework

The proposed model is shown in figure 2. This Figure introduces a summary of the approach which has done in this paper. First of all, the raw database that includes context of comments, is divided into sentences. Next step sentences are separated into subjective and objective sentences that will be explained below. This paper only focuses on the subjective statements. These sentences are tagged by Stanford POS tagger software then noun and adjective tags will be extracted. Product feature is taken from tagged noun by using Tf-idf factor and the polarity of the tagged adjectives is obtained by using SentiWordNet and the adjectives are known as an opinion. Finally, the user's satisfaction is achieved from the pairs of (attribute, opinion). In the following parts, description of each section will be thoroughly discussed.

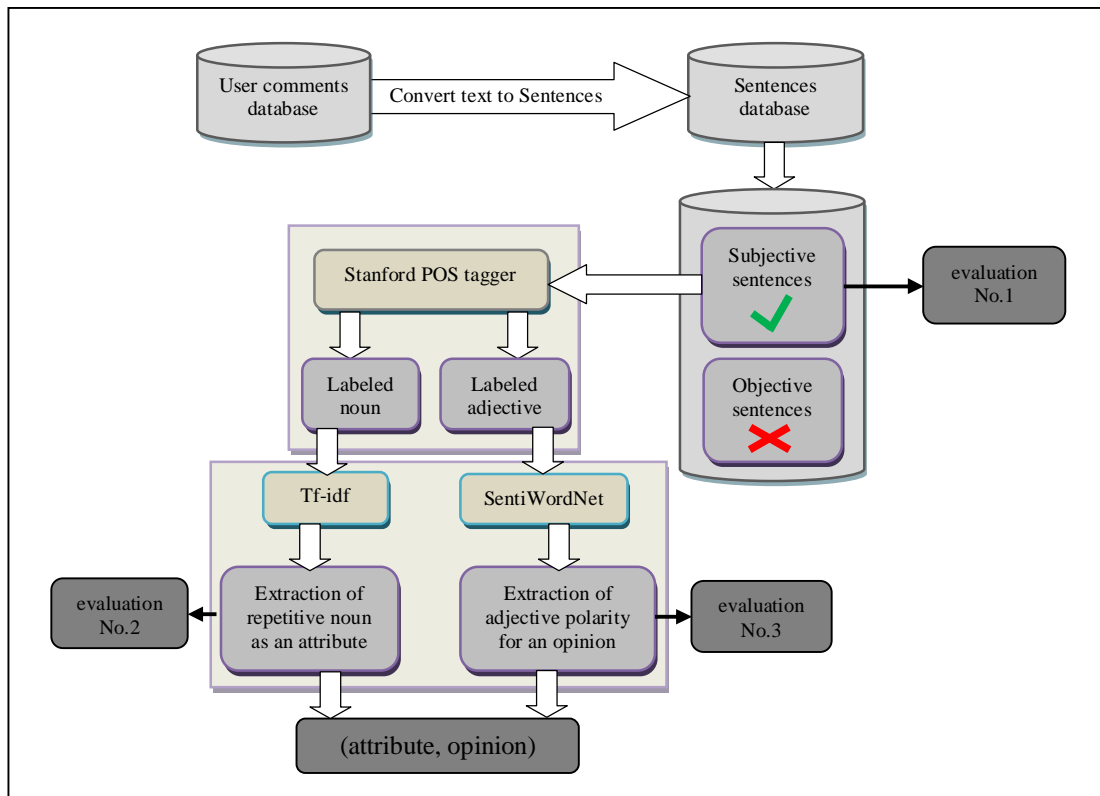


Figure. 2. Proposed model framework.

As shown in figure 2, after splitting the sentences, they are divided into two categories: subjective and objective, which are defined as follows: Subjective sentence: is a sentence which user describes his opinion about product feature. Objective sentence: is a sentence which user only tells news and there isn't any relationship with the specific product and also the sentences that user describes some information about product technical feature (Jafari and Minayi, 2012). "The photo quality is amazing" can be an example for subjective sentences and "I bought 2 of this model for Christmas presents" for objective sentences which exist in the database.

B. Part Of Speech Tagger

In this division, subjective sentences reflect the personal opinion of the users about the specific product. Therefore only a subjective statement can be used to analyze users' comments. First of all, subjective sentence is inserted in Stanford POS tagger software which was presented in the paper written by (Yi et al., 2003). The POS tagger software is a word tagger and shows the part of speech of each word in a sentence. This software is formed of 36 sections that each section shows the part of speech in a sentence (like noun, verb, adjective, etc). In this paper, the tagged noun (which is shown as NN, NNS, NNP, etc) and the tagged adjective (JJ, JJS, JJR, etc) are extracted by using this application. Schematic of the application is shown in figure 3.

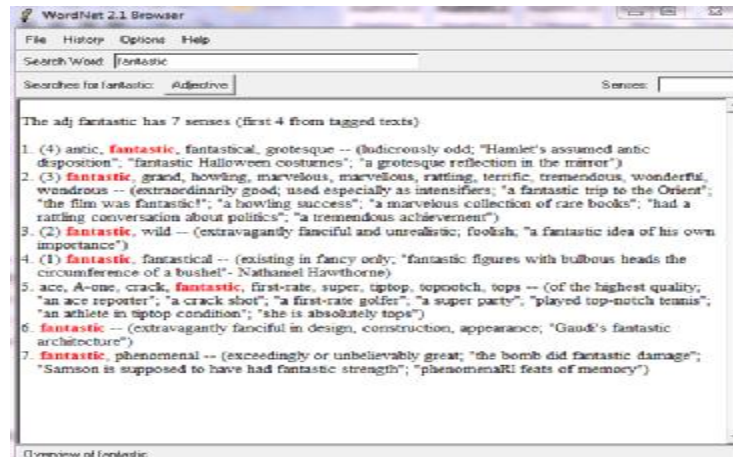


Figure. 7. An example of WordNet software.

After extracting synonyms for opinions, their polarity should be defined. Because positive or negative opinion represents the user's feeling about the product feature. Thus polarity of the opinion in context comments which were tagged by Stanford POS tagger, is determined by a software called SentiWordNet (Ohana and Tierney, 2009 ; Das et al., 2010). This application works in the range of [-1,1] that -1 means that word is negative, 1 means that word is positive and 0 is neutral. Figure 8 shows an example of this application.



Figure. 8. An example of SentiWordNet software.

III. Results and Analysis

After determining the polarity of the opinions by SentiWordNet and also identifying nouns that were mentioned as product feature, can reach a pair of word (attribute, opinion) which indicates that each feature includes how many opinion with the values of positive, negative and neutral. This approach is performed for five products separately and they are shown in figures 9, 10, 11, 12 and 13.

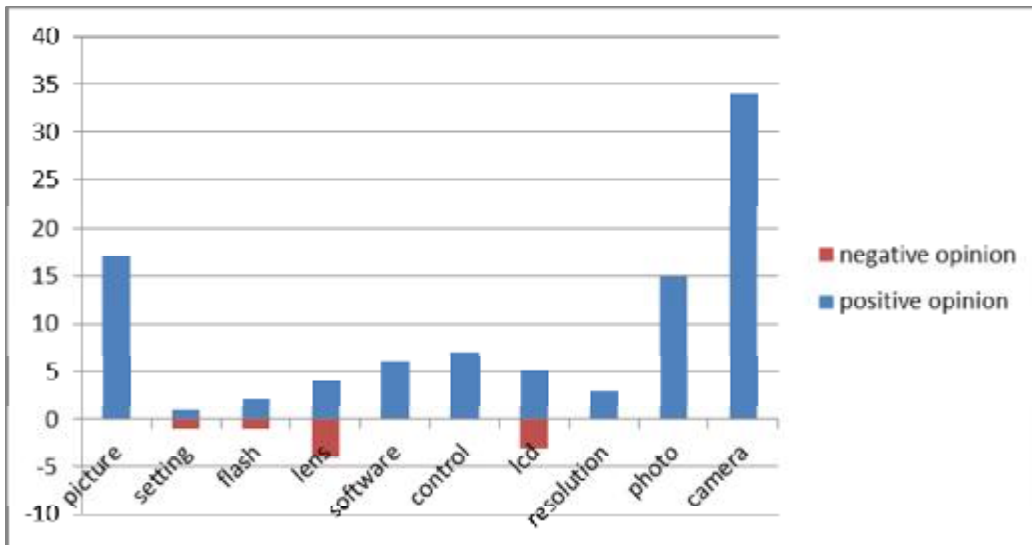


Figure. 9. Product No. 1 (Canon G3 digital camera).

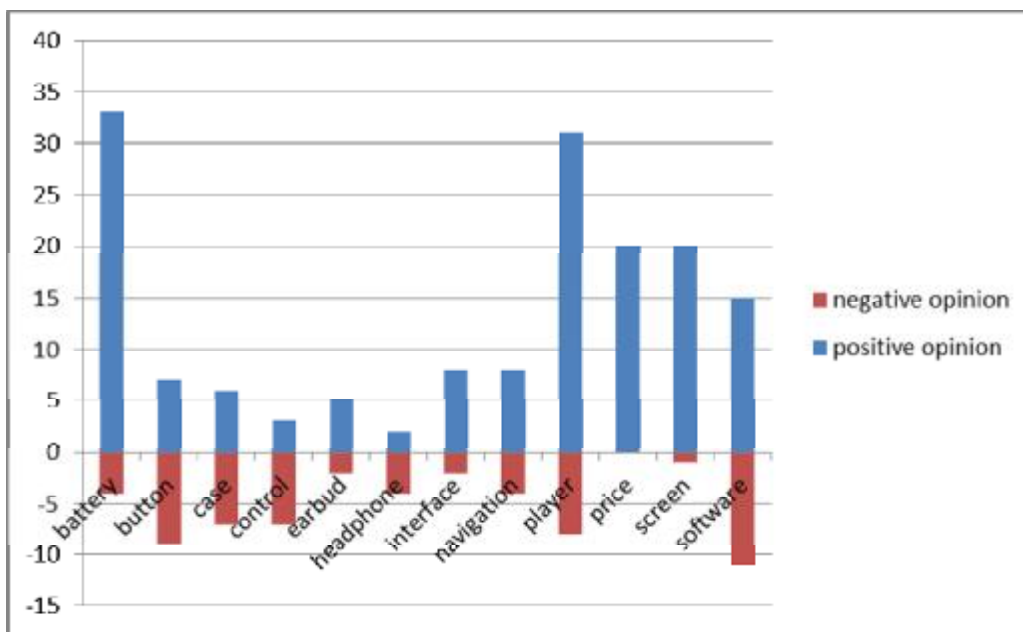


Figure. 10. Product No. 2 (Creative Labs Nomad Jukebox Zen Xtra 40GB mp3 player).

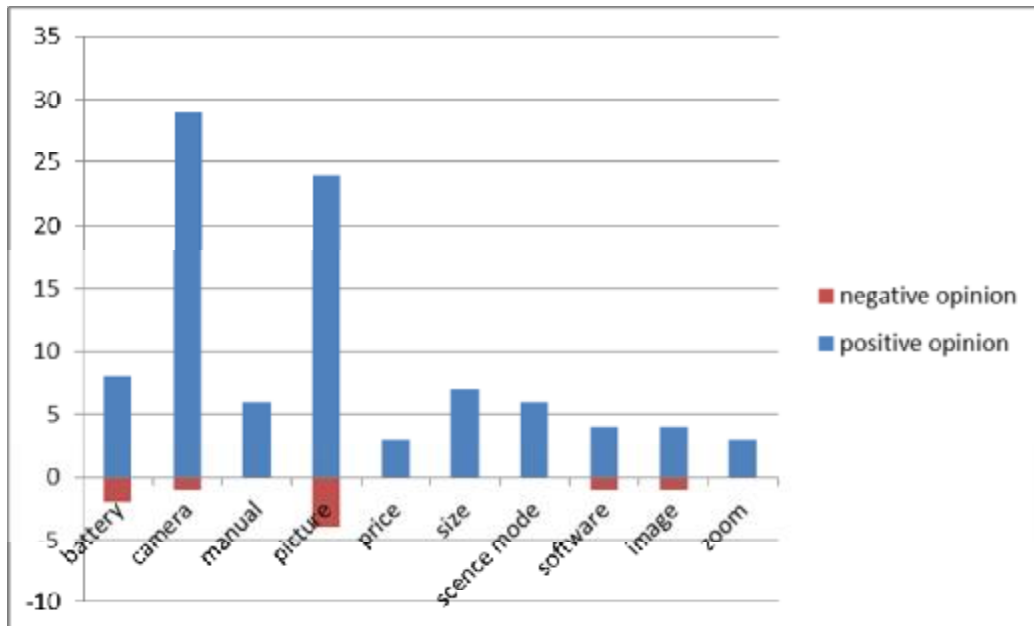


Figure. 11. Product No. 3 (Nikon coolpix 4300 digital camera).

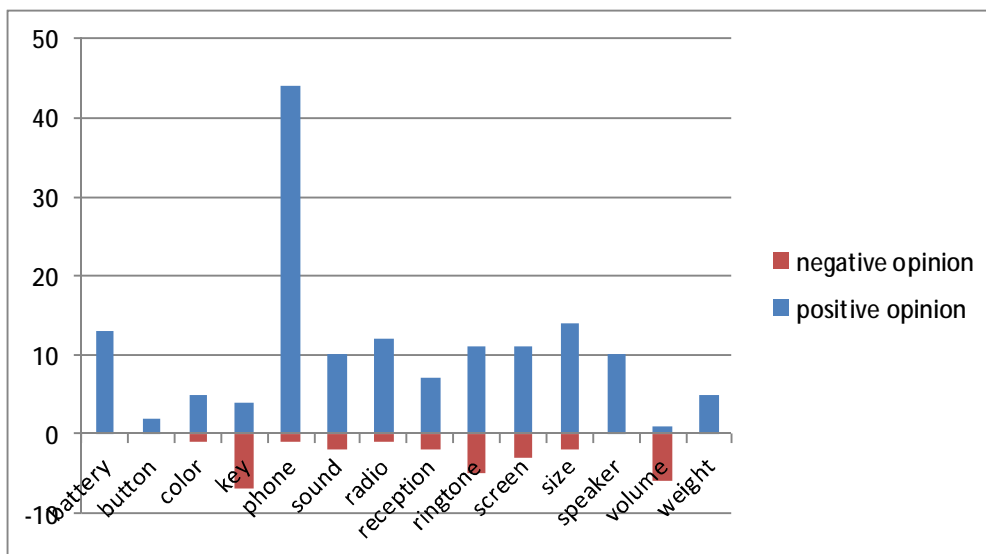


Figure. 12. Product No. 4 (Nokia 6610 cellular phone).

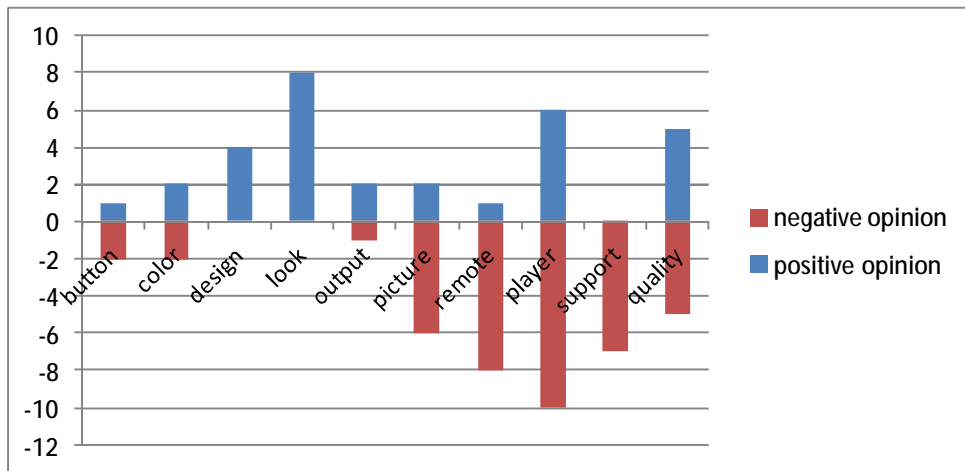


Figure. 13. Product No. 5 (Apex AD2600 Progressive-scan DVD player).

In this section, evaluation of collected opinions for five products that were taken from amazon.com, in order to indicate the accuracy of the research, is shown below. Table I indicates what percentage of the total sentences is subjective. Table II describes that what percentage of tagged nouns is product feature and finally, Table III shows what percentage of all adjectives are really opinion.

TABLE I
 EVALUATION OF SUBJECTIVE SENTENCES

*	F-measure	Recall	Precision
Subjective sentences	0.82	0.93	0.74

TABLE II
 EVALUATION OF PRODUCT FEATURE

Products	F-measure	Recall	Precision
digital camera: Canon G3	0.96	0.98	0.95
mp3 player: Creative Labs Nomad Jukebox Zen Xtra 40GB	0.91	0.88	0.95
digital camera: Nikon coolpix 4300	0.85	0.8	0.9
celluar phone: Nokia 6610	0.86	0.88	0.85
dvd player: Apex AD2600 Progressive-scan DVD player	0.7	0.81	0.62



TABLE III
EVALUATION OF OPINIONS

Products	F-measure	Recall	Precision
digital camera: Canon G3	0.88	0.93	0.84
mp3 player: Creative Labs Nomad Jukebox Zen Xtra 40GB	0.91	0.93	0.9
digital camera: Nikon coolpix 4300	0.91	0.95	0.88
cellular phone: Nokia 6610	0.87	0.87	0.88
dvd player: Apex AD2600 Progressive-scan DVD player	0.86	0.87	0.86

IV. Conclusions

Nowadays, people generally share their opinions about purchased goods on websites or social networks. People opinion about a subject, indicate personal feeling towards the topic. Opinion mining and sentiment mining can help the producers of the product in order to make customers more satisfied. Therefore this paper tries to provide a way to extract and evaluate customer satisfaction about a product. Method of this paper is that unprocessed raw data of the user's comments about the products is classified in a database. Then paragraphs are converted into sentences and subjective statements and objective statements are divided in order to explore subjective sentences that are derived from personal comments. Next, adjectives and nouns are extracted from subjective sentences. Adjectives polarity and repetitive nouns that are known as product feature, are described. Then the pair (attribute, opinion) for each product is made of obtained information. The evaluation shows that this approach has high accuracy. For future work, verbs in the sentences can be extracted and analyzed. So the user's opinions will be more accurately evaluated.

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