Volume 4, Issue 5, May 2014 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Feature and Opinion Identification for Online Digital Camera Reviews

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Abstract*- With the rapid growth of e-commerce, more and more products are sold on the Web, and more and more people are buying products on the Web. In order to improve customer satisfaction and their shopping experiences, it has become a common practice for online merchants to enable their customers to review or to express opinions on the products that they buy. With more and more common users becoming comfortable with the Internet, an increasing number of people are writing online reviews. As a consequence, the number of reviews that a product receives grows rapidly. Some popular products can get hundreds of reviews at some large merchant sites. This makes it very hard for a potential customer to read them to help him or her to make a decision on whether to buy the product. So to improve the sentiment analysis classification we proposed the architecture of feature based sentiment classification which consists of total four modules and these modules works on online reviews extraction from website TestFreaks.com for five different products of digital cameras. Our overall goal is to search for opinions about features of a target product from a collection of customer review data, analyse the opinion sentences, determine the orientations of the opinions, and provide a summary to the user.

***Keywords*-NLP, Parser, feature-based opinion mining, feature extraction, features refinement.**

I. Introduction

We found from literature survey that a lot of work has been done on sentence and document level opinion mining and some work has been done on feature based opinion mining. The Chinese author Bing Liu has played a major role in this research related to Sentiment analysis. He had also published a book “Sentiment Analysis and Opinion mining” on 22nd April, 2012. In his book he explained about sentiment analysis classification started from sentiment to spam detection by referring around 400 reference papers [1]. The opinion mining has been done at three levels a) Sentence based Level mining b) Document based Level mining c) Feature based level Mining(Aspect Based level mining).

But our focus is on feature based opinion mining. Because sentiment classifications at both document and sentence level does not find what the opinion holder liked and disliked. A negative sentiment on an object does not mean that the opinion holder dislikes everything about the object. Similarly, a positive sentiment on an object does not mean that the opinion holder likes everything about the object [2]. Thus, sentiment analysis at the feature level is necessary.

Objectives achieved from proposed methodology:

1. The document level and the sentence level analysis do not discover what exactly people liked and disliked. By using Feature based analysis we have achieved relationship between features and opinions which discovers finer-grained analysis.
2. Existing work for feature based mining does not contain Feature Refining phase. We have considered feature refining phase before NLP (Natural Language Processing). This helps us to remove the stop words from extracted reviews.
3. Performance evaluation has been done on static databases on the other hand we have worked on online reviews. (Website used in the project for reviews extraction is from Testfreaks.com).

II. System Design Framework

Previous studies on feature-based opinion mining have applied various methods for feature extraction and refinement, including NLP and statistical methods. But, most systems select the feature from a sentence by considering only information about the term itself, for example, term frequency, not bothering to consider the relationship between the term and the related opinion phrases in the sentence [3]. To resolve these problems, we proposes an enhanced method called, feature extraction and refinement [4]. The purpose of the analysis is to extract, organize, and classify the information contained in the required documents. In this section, we present the architecture and functional detail of the proposed opinion mining system to identify feature-opinion pairs [5]. Figure 1 presents the complete architecture of the proposed opinion mining system which consists of different functional modules.

This system has been used for Standard English language and local English language which provides us the comparison between two different types of texts formal and informal [6].

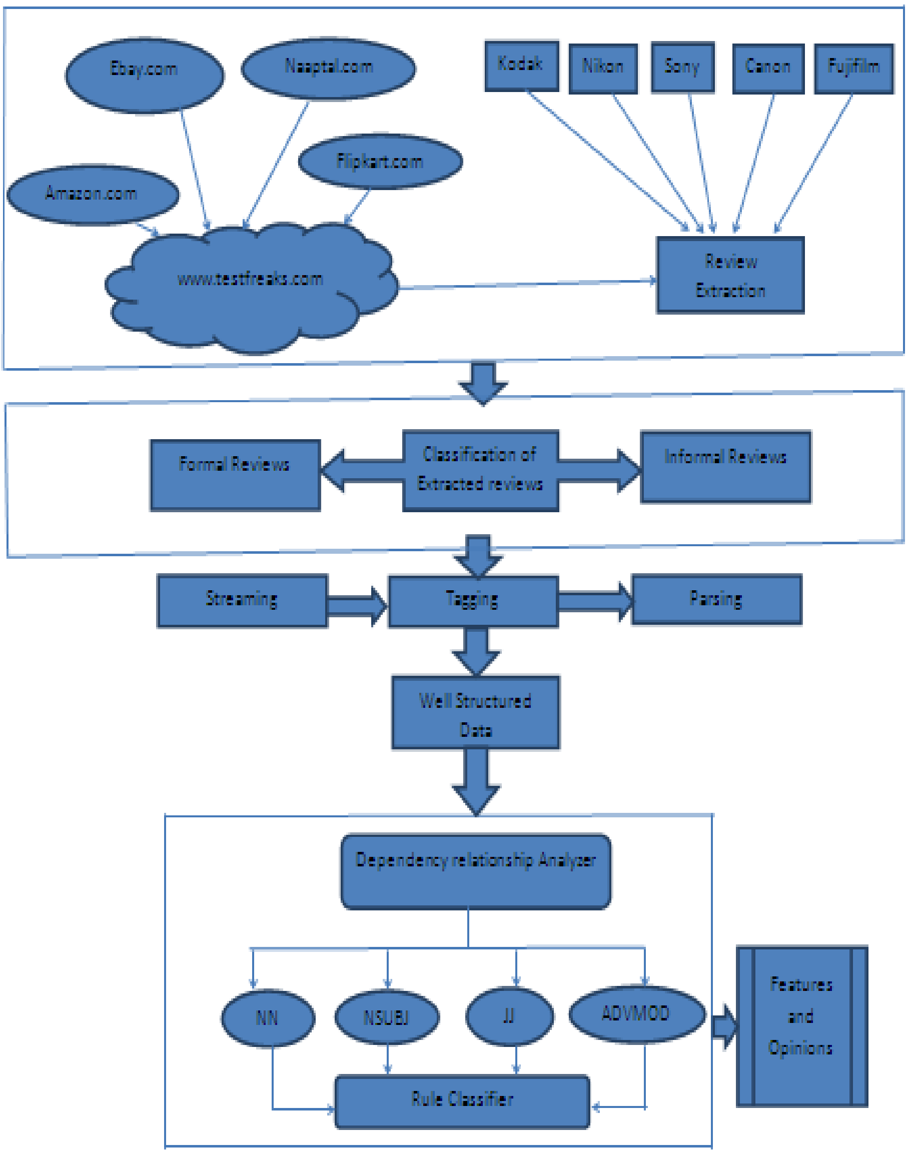

Figure 1. The Proposed System Architecture Framework

The overall process of FITM consists of four modules as follows:

- Pre-processing module
- Classification of Formal and Informal text module
- Refining module
- Feature extraction and opinion identification module

A. Working and module details of the proposed method architecture

Standard English Language:
Module 1 :(Pre-processing) This module extracts the online reviews from the website **www.testfreaks.com** which contains the dataset of four different online websites.Here I have considered five different products of digital camera as Nikon, Sony, Kodak Fujifilm, Canon etc. Filter has been provided to select any one of the product and after selecting the product name it will display all the reviews related to that particular product. But Reviews are not extracted as it is; actually it reads all the sub links of the master website (testfreaks.com) as per the selected filter and finally it displays the summary information of the reviews.
Module 2:(Classification for Formal and Informal Reviews) After review extraction module filtered review document are classified into three sets as formal reviews, Informal reviews and undefined reviews according to formal and informal data dictionary. This is assign as input document for next module.

Module 3 :(Refining module) After classification module classified review document is assign as input for refining phase which is a part of NLP (Natural language Processing) [7].Refining module consists of three stages streaming, tagging, and parsing which has been explained in detail as follows.

- **Streaming: -** This is the process of cleaning of data which removes the stop words from the extracted document. We have made dictionary for the stop words which contains total 600 stop words in that.

- **Tagging: -** We use Part Of Speech (POS) tagger to assign POS tags to words in a sentence (such as: tags for nouns, verbs, and adjective). To implement this process we use Stanford Tagger. This tagger is based on a technique that has been effective in a number of natural language applications which include part of speech and word sense tagging, prepositional phrase attachment, and syntactic parsing [8].

- **Parsing**: A natural language parser works out the grammatical structure of sentences, for instance, words which are grouped together are "phrases" and the Stanford parser identifies words as subjects or objects of a verb [9].

Module 4 :(Feature Extraction and Identification) This module is responsible to analyse dependency relations generated by document parser and generate all possible information components from them. The dependency relations between a pair of words w1 and w2 is represented as relation type (w1; w2), in which w1 is called head or governor and w2 is called dependent or modifier. In this way the feature and opinion identifier module is implemented as a rule-based system, which analyses the dependency relations to identify the features and opinions from review documents. Based on the observations of parsing and tagging of refining module, we have defined two different rules to tackle different types of sentence structures to identify information components [4]. A summarized representation of these rules is presented in the following paragraphs.

- **Rule-1:** In a dependency relation R, if there exist relationships nn(w1;w2) and nsubj(w3;w1) such that POS(w1) = POS(w2) = NN_, POS(w3) = JJ_ and w1, w2 are not stop-words, or if there exists a relationship nsubj(w3;w4) such that POS(w3) = JJ_, POS(w4) =NN_ and w3, w4 are not stop-words, then either (w1;w2)or w4 is considered as a feature and w3 as an opinion [10].
- **Rule-2:** In a dependency relation R, if there exist relationships nn(w1;w2) and nsubj(w3;w1) such that POS(w1) = POS(w2) = NN_, POS(w3) = JJ_ andw1, w2 are not stop-words, or if there exists a relationship nsubj(w3;w4) such that POS(w3) = JJ_, POS(w4) =NN_ and w3, w4 are not stop-words, then either (w1;w2)or w4 is considered as the feature and w3 as an opinion. Thereafter, the relationship advmod(w3;w5) relatingw3 with some adverbial word w5 is searched. In case of presence of advmod relationship, the information component is identified as < (w1; w2) or 4; w5; w3 > otherwise < (w1; w2) or w4;-; w3 > [10].

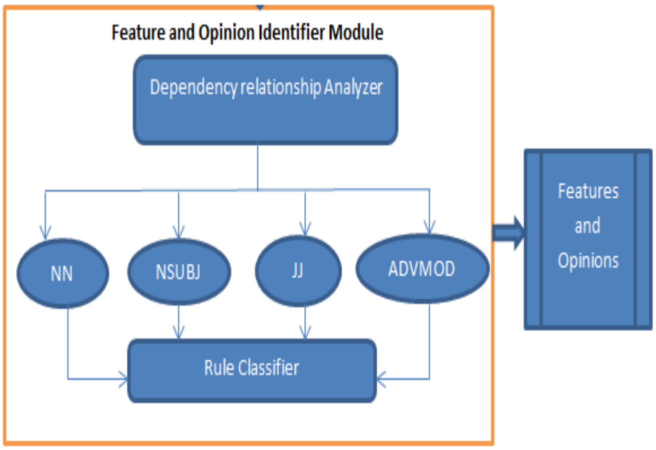

Figure 2.Feature and Opinion Identification

Local English Language:
Implementation for local English language has been done by using same modules as we have implemented for Standard English language but for this we have made one data set which contains the informal reviews for local language. Existing system does not considered informal words like ur, grt, gud and these types of words are removed before given to parser module and due to that the performance is degraded. So to overcome this problem wherever we found the informal word in the reviews our system convert that word into formal word and then it is forwarded to the Tagger and parser module. Following is the example of formal and informal words.
Example:awsm@awesome,luv@love,wlcm@welcome,gud@good,grt@great etc.

III. IMPLEMENTATION

A. EXPERIMENTAL DATA AND RESULTS

Formal and Informal Classification for Standard English language: We selected camera reviews for five different products from the link www.testfreaks.com which collects the data from multiple shopping websites for no of different products mentioned in. We ultimately select 159 online reviews for five different products of digital camera from the link mentioned above. Then we have used classification module which classifies the extracted reviews in formal and informal. The distribution of the scores of the 159 reviews has been showed in following Table I.

Table I: Online review classification

Name of the products	Total No of Reviews	Informal Reviews	Formal Reviews	Undefined Reviews
Nikon	37	36	1	0
Canon	40	34	4	2
Sony	45	39	5	1
Kodak	24	19	4	1
Fujifilm	13	09	3	1

Graphical representation for above results has been shown in following figure3 from which we can observe that informal reviews are more than formal reviews.

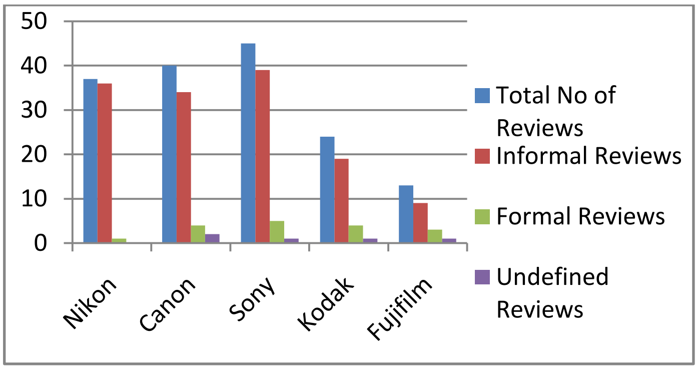

Figure 3. Formal & Informal Reviews Classification

Feature and Opinion Identification Standard English language: After classification of formal and informal reviews the classified data further given to refining module. Refining module undergoes in three stages Streaming, Tagging and Parsing and then parsed data has been given as input for last module which provides us a summary of features and related opinions. Results for the same have been shown in Table II.

Table II: Feature and Opinion Identification

Name of the Product	Total No of Features	Total No of Opinions
Nikon	08	19
anon	07	14
Sony	12	17
Kodak	11	16
Fujifilm	07	11

Following figure 4 shows the graphical representation of features and related opinions.

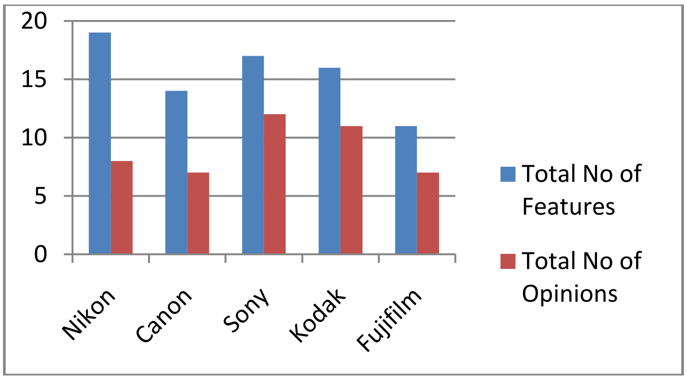

Figure 4. Graphical representation for feature and opinion identification

Results of Feature Extraction Module for Local English Language by using testfreaks.com website:
Following table shows total no of features that has been collected from data set that has been manually prepared.

Table III: Feature and opinion identification for Informal Text

Name of the Product	Total No of Features	Total No of Opinions
Nikon	12	08
Anon	10	07
Sony	12	09
Kodak	10	08
Fujifilm	11	07

Graphical representation for above results has been shown in following figure5.

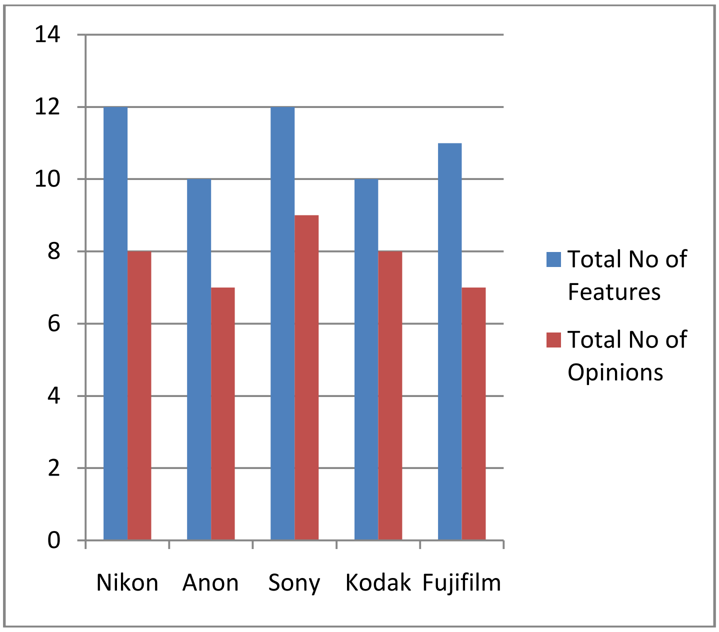

Figure 5. Graphical representations for feature and opinion identification for local language

III. PERFORMANCE EVALUATION

Performance Evaluation of our proposed method can be done by using Precision and Recall measures. These two measures can be calculated by using following equations. This precision measure evaluates the ratio of correctly extracted features by the system. In following equation, 'correct feature' indicates the feature that coincides with the manually tagged feature under human supervision for the experiments. Although both 'precision' and 'recall' are important evaluating criteria, we thought that 'precision' is more appropriate measure based on the observation that, in summarization, it is more important to provide the correct and exact feature information to the user than to provide complete information without missing features.

$$\textbf{Precision} = \frac{\textbf{No.of correct features extracted by the system}}{\textbf{No. of features extracted by the system}}$$

$$\textbf{Recall} = \frac{\textbf{No. of correct features extracted by the system}}{\textbf{No. of correct features}}$$

Performance can be evaluated based on the experimental data and results which we got in previous section.

Note: Values for No of correct features available (Ca) have considered as 10 for digital camera as follows.
(Battery life, camera, hunting, user, money, weight, screen, light, start-up, image)

Performance Evaluation for Standard English Language and Local English Language:- Following Table IV shows total no of correct features available that is denoted as Ca which contains the fixed value as 10 as mentioned above in note. Number of features extracted by the system is denoted as Fs and number of correct features extracted by the system as

CS. Calculation for the precision and recall values has been done by using above parameters and in further results these values are used for the comparison between Standard English language and local English language.

Table IV: Feature extraction of Both Languages

Name of the Products	No. of Correct Features Available (Ca)		No. of features Extracted by System (Fs)		No. of correct features Extracted by System (Cs)	
	Std Eng Lang	Local Eng Lang	Std Eng Lang	Local Eng Lang	Std Eng Lang	Local Eng Lang
Nikon	10	10	08	12	07	08
Canon	10	10	07	10	06	07
Sony	10	10	12	12	08	09
Kodak	10	10	11	10	08	08
Fujifilm	10	10	07	11	06	07

Following Table V shows Precision and Recall values for Standard English language and local English language.

Table V: Precision and Recall values of Both Languages

Name of the products	Precision (Cs/Fs)		Recall (Cs/Ca)	
	Std Eng Lang	Local Eng Lang	Std Eng Lang	Local Eng Lang
Nikon	7/8= 0.87	8/12= 0.66	7/10=0.70	8/10=0.8
Canon	6/7=0.85	7/10=0.70	6/10=0.60	7/10=0.7
Sony	8/12=0.66	9/12=0.75	8/10=0.80	9/10=0.9
Kodak	8/11=0.72	8/10=0.80	8/10=0.80	8/10=0.8
Fujifilm	6/7=0.85	7/11=0.63	6/10=0.60	7/10=0.7

Following figure 6 and figure 7 shows comparison of precision values and recall values for both type of language. From these graphs we can conclude that precision values for Standard English language is more than local English language. Recall values for local English language is more than the Standard English language.

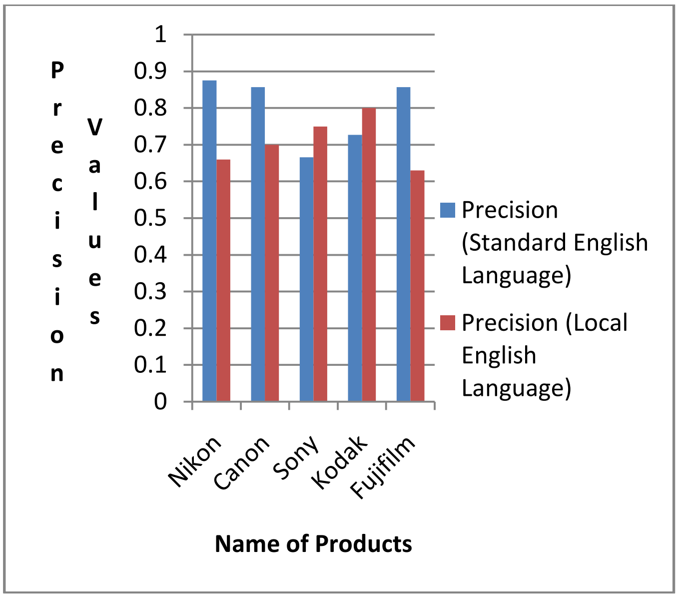

Figure 6. Graphical representations for Comparison of Precision values

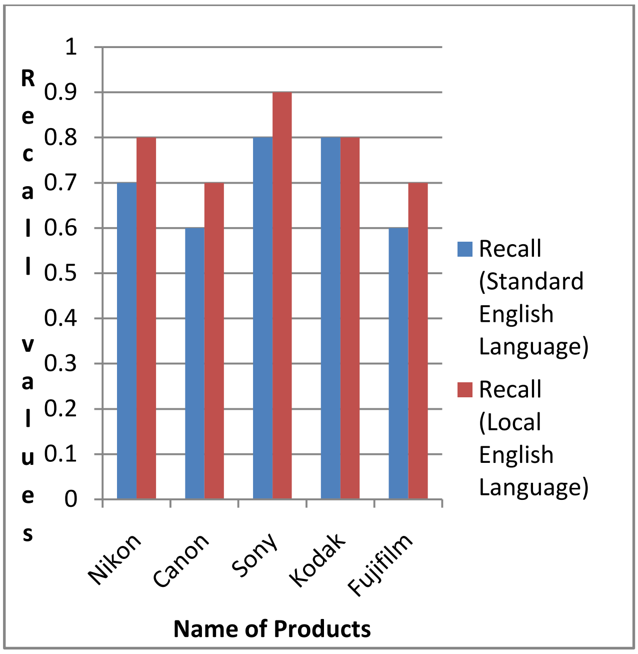

Figure 7. Graphical representations for Comparison of Recall values

Conclusions

Proposed system called enhanced Feature Extraction and Refinement for Informal Text Mining (FITM) has been used for sentiment analysis classification. This system module has been used for analysing customer reviews data related to five different digital camera products. FITM is highly effective which extracts the online reviews from the website that is testfreaks.com and classifies these reviews as formal and informal texts. It also refines the features by using streaming, parsing and tagging methods, which analyses the dependency relations to identify the features and opinions from review documents and this improves sentiment analysis classification. This system is also works with informal texts for local language and that is one of the main objectives of our project. We have also evaluated the performance by using precision and recall parameters for both types of languages standard and local English languages.

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