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# Customer Reviews and Analysis using Opinion Mining Adaptive Algorithm

Palla Pavankumar[1], Tippani Gayathri[2], Kathi Venkataramana[3]

Assistant Professor, Dept. of Computer Engineering, Keshav Memorial Institute of Technology, Narayanaguda, Hyderabad, India[1]

Assistant Professor, Dept. of Computer Engineering, Keshav Memorial Institute of Technology, Narayanaguda, Hyderabad, India[2]

Assistant Professor, Dept. of Computer Science & Engineering, Geethanjali Institute of Science & Technology, Nellore, India[3]

**ABSTRACT:** The important part to gather the information is always seems as what the people think. The growing availability of opinion rich resources like online review sites and blogs arises as people can easily seek out and understand the opinions of others. Users express their views and opinions regarding products and services. These opinions are subjective information which represents user's sentiments, feelings or appraisal related to the same. The concept of opinion is very broad. In this paper we propose an opinion mining adaptive algorithm (OMAA) focuses on the Classification reviews on customer reviews that conveys user's opinion i.e. positive or negative at various levels. The OMAA is to predicting opinions enable us, to extract the sentiments from the web for online customer's preferences, which could prove valuable for marketing research. Much of the research work had been done on the processing of opinions or sentiments recently because opinions are so important that whenever we need to make a decision we want to know others' opinions. This opinion is not only important for a user but is also useful for predicting the online marketing purchases and improving impacts on products and sales.

**KEYWORDS***:* Opinion Mining, Sentiment Analysis, Mining Classifications, Web Mining

## I. INTRODUCTION

We Opinion mining is a type of natural language processing for tracking the attitudes, feelings or appraisal of the public about particular topic, product or services. Textual information in the entire world is of two types: facts and opinions. The facts are the objective expressions which describe the entities, events and properties whereas the opinion is the subjective expression which describes people's opinions, emotions and sentiments towards entities and their properties. The current search engine searches for facts because they assume the facts are true and can be expressed with keywords. But these search engines do not find the opinions because opinions or sentiments are very difficult to express by keywords and that is why there ranking strategy are not appropriate for opinion retrieval. Now, the web has significantly changed its way that people comments their views and opinion on any product and services. User can post their comments on any internet forums, review sites, blogs and discussion group which are commonly known as user generated content which contains the important information. This online word- of- mouth behaviour represents new and considerable sources of information and their applications. These online comments are not limited to our friend circle but it is also expanded on a global or web scale. Today, if the user wants the views on a particular product he/she has no longer limited to ask their friends because they got the opinion for that product on the internet through various reviews or comments. In the same if the organization wants the opinion of their products and services they use these user generated contents from the web for the review or comments of their products and services.

The art Opinion Mining is to recognize the subjectivity and objectivity of a text and further classify the opinion orientation of subjective text. In short we say that Opinion Mining[19] is an automated extraction of subjective content from text and identifying the orientation such as positive or negative in that text. It aims to explore feelings of a person

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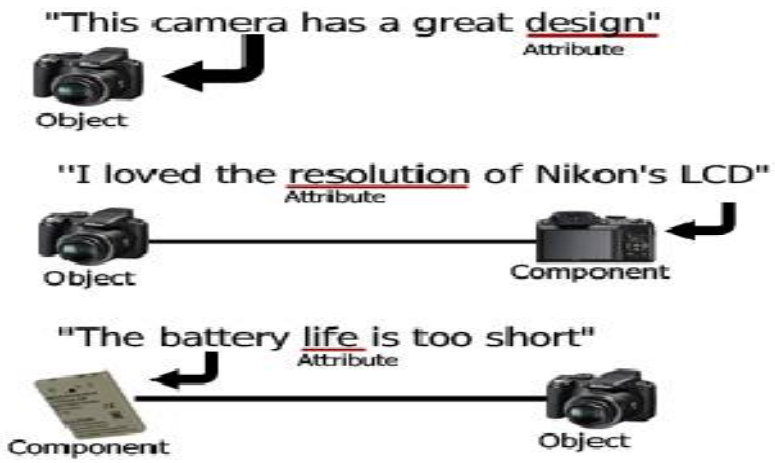
who write the text. It used Natural Language Processing and Machine Learning ethics to determine opinion in the text. The evaluation of opinion can be done in two ways:

- Direct opinion, gives positive or negative opinion about the object directly. For example, "*The picture quality of this camera is poor*" expresses a direct opinion.
- Comparison means to compare the object with some other similar objects. For example, "*The picture quality of camera-y is better than that of Camera-x*." expresses a comparison.

### 1.1 Defining Opinion Components in a Opinion Mining Context

The definitions used in this section were proposed in [9], and they summarize important elements that compose an opinion. Some of these definitions are just a naturalobservation of elements present in opinions, while others refer to definition of problemsaddressed in [9]. For this reason some of these definitions may not apply to otherworks as they can differ a lot from their goals as well as from the strategies they employ toachieve them.

### 1.1 Defining Opinion Components in a Opinion Mining Context




## II. RELATED WORK

One of the reasons why some search engines are so successful on the Internet are their commitment to quality services, especially with regard to the processing speed of usersqueries. In today's Internet, with billions of available pages, the lack of mechanismsthat provide a response in a short amount of time would leave the system incompatiblewith the standards of the modern times (more data must be processed with even morestringent constraints with respect to time). The main names behind search engines (e.g,Google, Yahoo, Bing, etc.) achieve this high standard of service mainly due to their indexing technique combined with high end infrastructure comprised of several hundredsof clusters highly optimized for jobs demanding large capacity of computational work. A ranking algorithm provides a hierarchical level of more important documents, thereby providing an initial clue to the user about where the desired informationis more likely to be.During a search operation the following interactions are performed, as shown in figure 2.1: (1) A query is submitted by the user. (2) The user query is checked to ensurethat it is ready to be used by the retrieval system. This could be achieved throughsimple tasks such as removing stopwords", reducing the words to roots (stemming)and checking the spelling. (3) The query is checked against the available indexes inorder to retrieve the documents thatcontain some of the query terms. Afterwards, aranking algorithm is applied to the set of found documents which are finally presentedto the user (the most relevant documents appear at the beginning of this list). (4) Theuser receives the response and accesses the matching documents from a result list.

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**2.1 Web Content Mining**

Web content mining is very important as it deals directly with information. The goal isto mine content from web documents in order to build knowledge from it. This knowledge can be either hidden or somehow simply difficult to be analyzed in a straightforward way. Next subsection will introduce an important field of Web Content Miningcalled Opinion Mining.

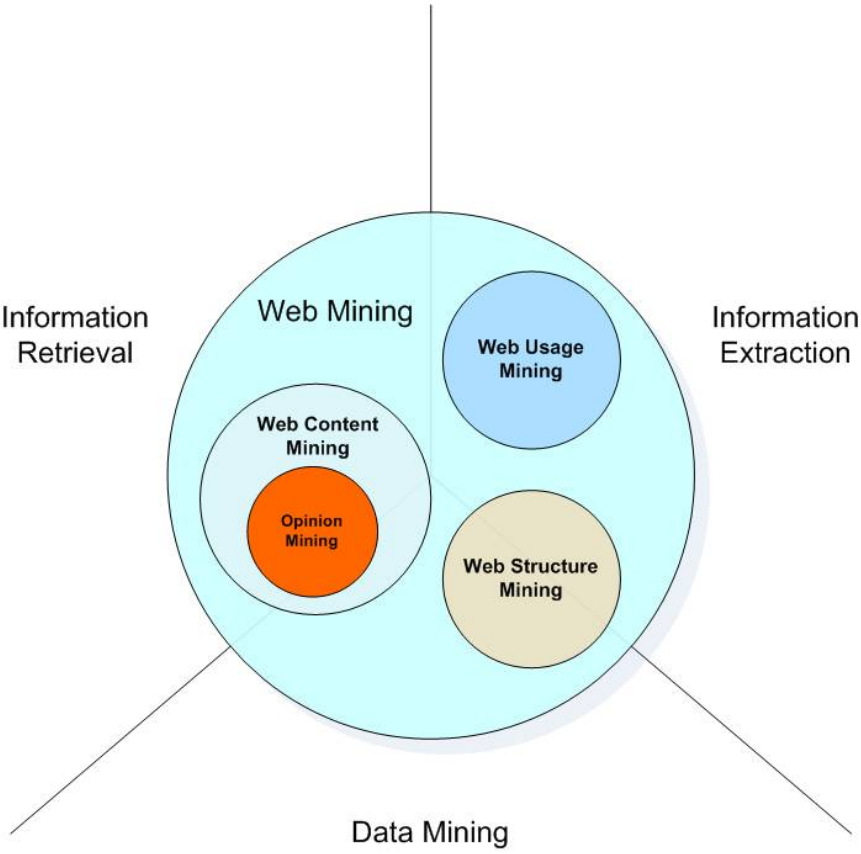


**Fig 2.1: Information retrieval systems.**

**2.3 Opinion Mining**

Opinion Mining is a field of Web Content Mining that aims to find valuableinformationout of users opinions. Mining opinions on the web is a fairly new subject, and its importance has grown significantly mainly due to the fast growth of e-commerce, blogsand forums. With the high profits of e-commerce increasing year after year many people had
changed the habit of going to a shop for the comfortable virtual shopping. Eitherways,searching for useful information on users opinions before purchasing a product,became a common practice for many people. A major problem however, is findingthe desired information on them. It is not difficult to find web sites with thousandsof reviews for a single product, and thus finding an useful information among them can be a very difficult task. For example, a new customer may be interested in reviewsthat talk about many features of a certain camera. However, old customers of a specificbrand, may be interested only in what people have to say about the auto focus functionof a newly released model.From the business perspective getting important information out of opinions canrepresent a good source of advertisement or product feedback. For example, a website specialized on electronics reviews could place advertisements on their pages basedon consumer opinions. For instance, if the majority of users express negative

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opinionsabout a given product, the web site could place ads from an alternative product froma competitor. Also, manufacturers can get the feedback of their products to improvetheir products or services.

## III. SYSTEM ARCHITECTURE

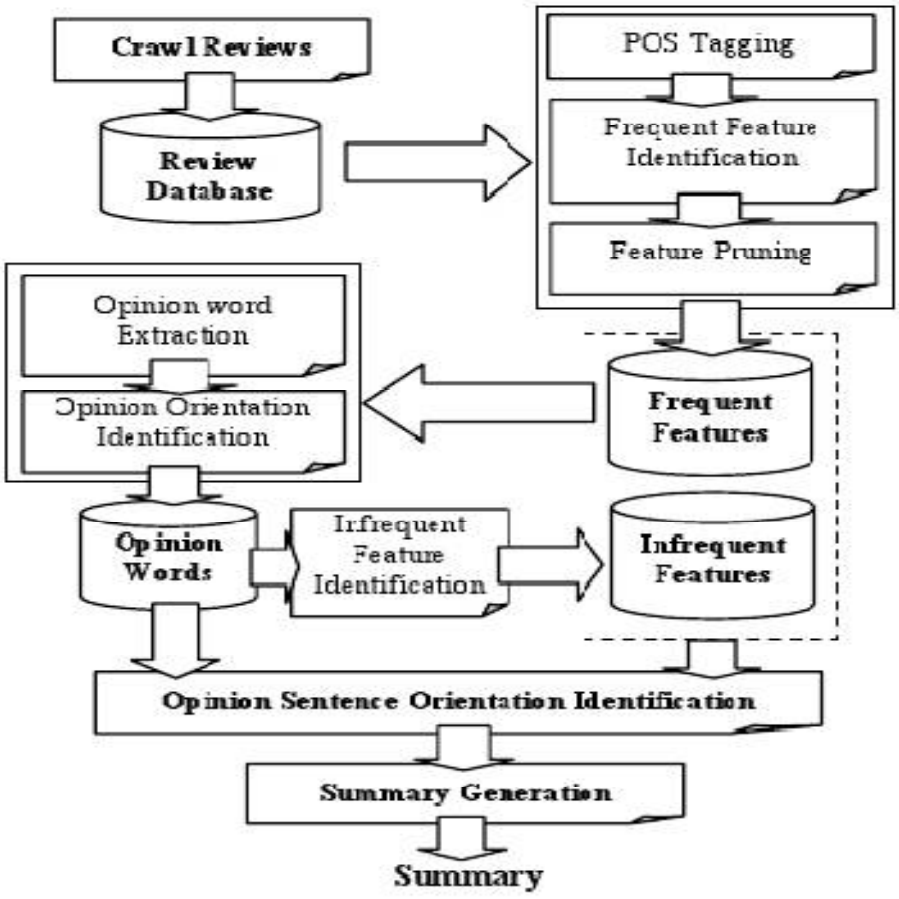


**Figure 3: Architecture of an opinion mining system**

The system counts with a crawling module, which first downloads all the reviews
and stores them in the database. After that a POS tagger tags all the reviews whichwill work as hooks for the mining part responsible for finding frequent features. Thisstep is skipped by some systems which employs manual feature annotation as in [21],where ontologies were used to annotate movies features manually. Next, with thetagged sentences and features identified, opinion words are extracted and their semantic orientation is identified with the help of WordNet. Now with opinion words identifiedand extracted, the system identifies infrequent features.

## IV. ANALYSIS

### 4.1 Feature Identification

Feature identification is the process used to deduce possible product features out of
the tagged texts generated by the last step. Both [15] and [9] use some heuristics tonarrow words that are more likely to be a feature inside a sentence. Normally, thepart-of-speech responsible for giving names to entities of the real world are nouns, inthis case a noun gives name to the product and its features (i.e zoom, battery life,image quality, etc.). In these works, they define two categories of features, frequentfeatures and infrequent features.In [21] Ontology Based Opinion

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Mining for Movie Reviews", an ontology basedapproach was used to extract features from opinions. In they work, they experimentedit with movies reviews, where they identified sentences containing the ontology terminologies.

Here it is important to differentiate between the two approaches with their prosand cons. In [15] and [9], feature identification is performed automatically. The greatadvantage of this method is to perform the whole process automatically, with minimalhuman intervention. The biggest downside however is that the output (the frequent features) depends a lot on the number of opinions being analyzed. Also, there is noguarantee that a frequent feature found by the system is actually a real feature. In [21]and other works where features were manually annotated, the advantage is that thesystem will always identify real features, being frequent or not. This will only dependon the correctness of the previously made annotation. The great downside however, isthat a great number of annotations have to be made. They may not be only specificto categories (such as digital cameras, video games, cellular phones), but they could be even more specific such as models of a specific brand (Nikon P90, Nikon D5000,etc). That would make the annotation of features a very hard work. Also, people maycomment on the lack of features of a given product, or they may use different words torefer to the same feature which a system with manual annotated features will fail torecognize.Given the short comparison between the different approaches above, the methodexplored in [15] and [9] will be further discussed, as it needs a minimal human intervention to perform its task reasonably well which could be later improved by othermethods.

**4.2 Frequent Features Identification**

In, [15] and [9] the proposed system extract only nouns or noun phrases (explicit possiblefeatures) from the text. In this step, the extracted nouns are called candidate features.

Then an association mining algorithm finds all the frequent itemsets, which are theset of frequent features (those ones that many users write about). The idea behindthis technique is that features that appear on many opinions have more chance to berelevant, and therefore, more likely to be actually a real product feature. The Apriorialgorithm [2] was used to generate the set of frequent itemsets. However, for this task there was no need of finding association rules among items, therefore only the part ofthe algorithm that finds frequent itemsets wasinteresting for these works. In [9] and[15], a minimum support of 1% was used.

**4.2.1 Infrequent Features Identification**

A very simple heuristic was used in [15] to discover possible infrequent features (the ones referenced by a small number of people), as the association mining is unable toidentify them.

**Example:**

I. "The pictures are absolutely amazing."
II. "The software that comes with it is amazing."

In the above example, the two sentences have one opinion word in common: amazing. Because an opinion word could be used to describe more than one object, theseopinion words are used to look for features which couldn't be found in the step describedon

```
for each sentence in the review database
  if (it contains no frequent feature but one or more opinion
      words)
  { find the nearest noun/noun phrase around the opinion
    word. The noun/noun phrase is stored in the feature
    set as an infrequent feature. }
```

**Figure 4.2.1: Infrequent feature extraction**

**4.3 Opinion Sentiment Analysis**

Sentiment classification or sentiment analysis is an area of study that aims to classify the sentiment encoded by texts as shown in the following example:

**Example:**

I. The girl is angry →negative

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II. The sun is absolutely beautiful today → positive

The word sentiment is a synonym for polarity and both are widely used to describethe orientation of texts, sentences and words as in example 4. This work will deal with sentiment classification of texts represented by users opinions, therefore the nameopinion sentiment.The analysis of sentiment can be performed on several levels of granularity (words,sentences, texts and documents). For many applications, classifying the sentimentof documents as a whole is sufficient, for others a finer level of granularity might benecessary.The work done by [18] and [22] classifies each user opinion as a whole. In [15] and [3] sentiment classification is done at the sentence level. In [9], each feature within aopinion has a sentiment associated. The reason why this last approach is preferablethan the others, is easy to realize through a simple observation. To illustrate it, thinkabout a specialized web site for cameras, where customers can write their opinions abouta certain product, as illustrated in figure 3.4. For example
the sentence: "I like my camera and the 24x zoom, but i think the battery life is tooshort". Here it is easy to realize that the sentence is "more positive than negative",however that would still hide one negative aspect of the camera under discussion. Thismay represent a very important piece of information, which can be obfuscated byclassifying the whole sentence as positive. For this reason the method explored by [9]achieves an optimal granularity level as it treats each attribute of an OuD with thenecessary details.

**4.3.1 Determining Sentiment of Opinions at the Sentence Level**

An opinion can be analyzed at different levels of granularity. In this work,
the approaches used to analyze the opinion as a whole are going to be discarded as in
[18] and [22].Therefore, thetwo remaining approaches with respect to their granularity, are going to be exposed with more details. Figure 4.2.1 shows a pseucocode which aims to find the sentimentof opinions at the sentence level. The next section, will analyze the sentiment of anopinion at the feature level, as proposed by [9], which is of greater importance for thiswork.

**4.3.2 Negation Rules**

A negation word such as no, not and never and also some words that follow patternssuch as *"stop"* + *"vb-ing"*, *"quit"* + *"vb-ing" and "cease"* + *"vb-ing"* change theorientation of opinion words in the following way:

I. Negation Negative →Positive
II. Negation Positive →Negative
III. Negation Neutral →Negative

Some examples for each negation rule defined above:

I. "no problem"
II. "not good"
III. "does not work"

**4.3.4 Determining Opinion Sentiment at the Feature Level**

In [9], after identifying all the opinion words for a given feature, the system calculates
the opinion orientation for each feature using the following equation:

$$\text{Score}(f) = \sum_{wi:wi \in S \wedge wi \in V}^{n} \frac{wi.SO}{dis(wi,f)}$$

- ***S*** is a sentence with a set of features
- ***wi*** is an opinion word
- ***V*** is the set of all opinion words(including idioms)
- ***wi.SO*** is the semantic orientation of opinion word ***wi***
- ***dis(wi, f)*** is the distance between feature f and opinion word ***wi*** in the sentence ***S***

For a sentence s that contains a set of features and for each feature f the aboveorientation score is computed. A positive word is assigned the orientation +1, and anegative one is assigned -1. In the above equation wi is an opinion

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word, V is the setof all opinion words (including idioms) and s is the sentence that contains the feature f,dis(wi; f) is the distance between feature f and opinion word wi in the sentence s. Thereason for the multiplicative inverse in the formula is to give low weights to opinionwords that are far away from the feature f. The pseudo code of figure 3 was used to find the opinion orientation at the feature level.

**OPINION MINING ADAPTIVE ALGORITHM (OMAA)**

for each sentence $S_i$ that contains a set of features do
features = features contained in $S_i$
for each feature $f_i$ in *features* do
*Adaption = 0;*
if feature $f_i$ is in the "but" clause then
*Adaption* = apply the"but" clause rule
else remove "but" clause from $S_i$ if it exists;
for each unmarked opinion word *OW* in $S_i$do
*Adaption* += ***word Adaption*** *(ow,* $f_{i,}$*,*$S_i$*);*
endfor
endif
if*Adaption* > 0 then
$f_i$'s Adaption in $S_i$ = 1
else if Adaption in $S_i$ < 0 then
$f_i$ *'s Adaption in* $S_i$ = -1
*else*
$f_i$ *'s Adaption in* $S_i$ = 0
endif
endif

## V. IMPLEMENTATION

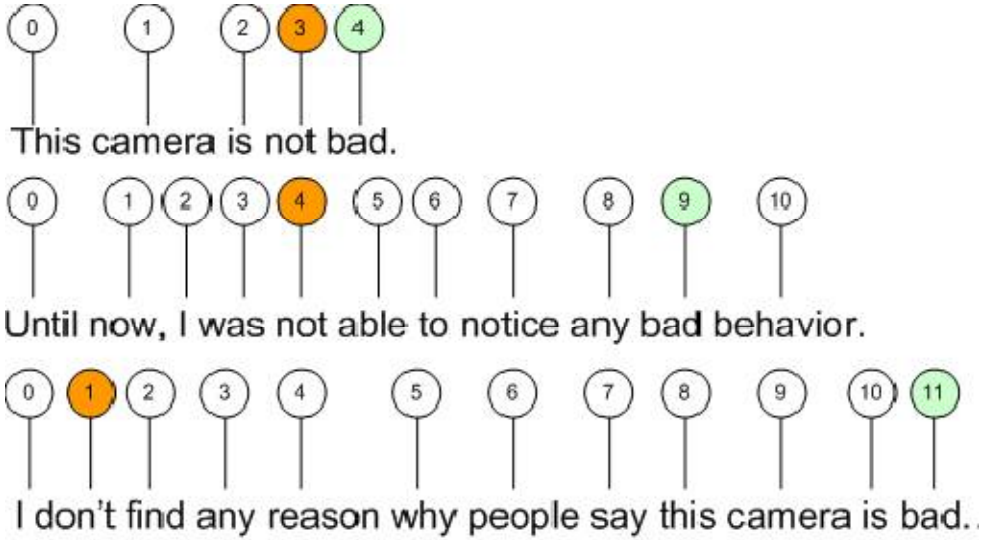


**Figure 5.1: Sentences with negation words**

To evaluate the effectiveness of the sentiment classification algorithm, the orientation associated with each feature in a sentence was analyzed manually in order to achieve a high degree of confidence. The result of this analyses is presented on the graph of figure 6.1 and table 6.2. A correctly classified opinion is either a

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negative or positive opinionfor a given feature, which was correctly identified by the system. All the features were identified automatically, and only the sentences with real features (frequent features)were analyzed. Sentences with candidate features were discarded. The effectiveness of the automatic feature identification algorithm will be discussed later on section 7.3.It is important to consider the complexity of judging (even for a human) whetheran opinion is positive or negative. There are many cases where this analyzes is pretty1ObjectSpace is a Ruby module used for memory management, which is disabled by default inJRuby. One of POECS libraries use this feature which can be enabled by passing the parameters-X+O. It has been reported by the JRuby developing team that ObjectSpace can create a substantial overhead and thus affecting the performance of the system.

**Table 5.1: Effectiveness of sentiment classification**

| Product | Correctly Classified Opinions | Opinion Sentences |
|---|---|---|
| Ipod Touch 8GB | 79% | 673 |
| Nikon D5000 | 82% | 452 |
| Nikon P90 | 84% | 273 |
| Xbox 360 | 73% | 181 |

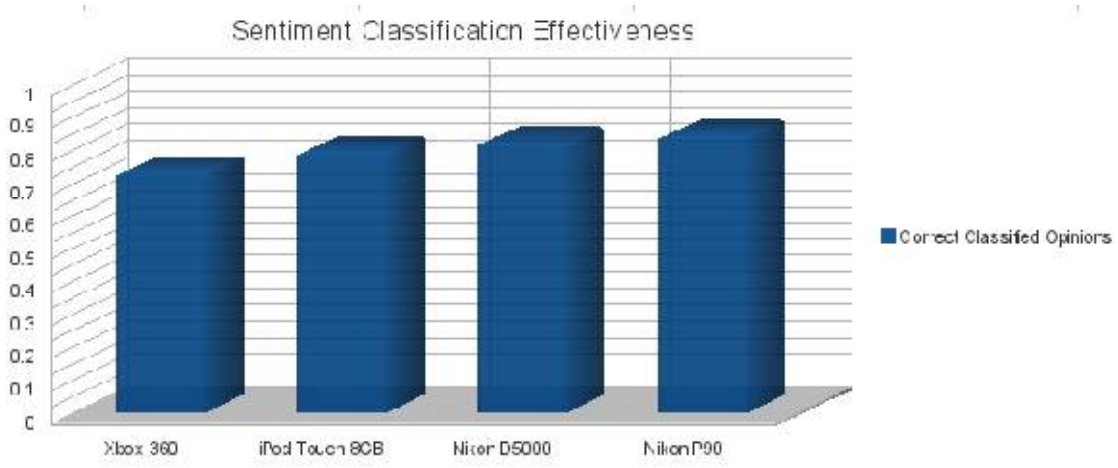


**Figure 5.1: Effectiveness of opinion sentiment classification**

## IV. EVALUATION

Straightforward, especially when explicit opinion words are used. However, in somecases, in order to understand whether an opinion is negative or positive, a domain specific knowledge is needed. Example 1 illustrates some of these cases:

**Example 1:**

I. "The iPod battery lasts for 5 hours with music and Wi-Fi turned on."

II. "The device heats very fast."

In sentence I, it is difficult to know whether a battery lasting for 5 hours underthe described conditions is positive or negative. In sentence II, heating fast depends alot of which device is being analyzed. For instance getting hot fast could represent anegative behaviour of an electronic device such as video games or notebooks. However,if the OuD is a portable heater or an electric oven, heating fast should be a positive behaviour.

There are also situations where wrong parts-of-speech are assigned to words andsince the POS tagging operation is the foundation of the whole mining process, a wrong tagging classification would directly affect the mining process, as shown in example 2:

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**Example 2:**

I. "This battery is really GOOD."

II. "[. . . ] hard drive of 120 GB which comes with the device."

In sentence I, the word GOOD is written in upcase, a common practice among internet users, which aims to emphasize sentiments. The POS tagger however interprets this word as belonging to the group of proper nouns. Therefore, the mining algorithmwill fail to recognize it as an opinion word. In this work, such cases were not coveredsince they are not common and hence addressing them would produce a great delay forthe mining tasks.A snippet of a customer opinion for Xbox 360 is shown in sentence II. It wasdetected that the POS tagger would fail to recognize hard drive as a noun group(feature). Unlike, the POS tagger interprets the word as follows: hard →adjective anddrive→noun. Thus, hard was taken by the mining algorithm as an opinion word.

## VI. CONCLUSION& FUTURE WORK

Opinions are a unique type of information which are different from facts. The methods for content classification based on ranking (like those used by search engines) are not effective or simply do not accurately depict reality, as one opinion is different frommultiple opinions.

During the evaluation of POECS it was possible to see that it is feasible and re liable to build system capable of classifying and organizing opinions through the so called feature based summary, which resumes themost relevant information for users. However, it is undeniable that a great number of opinions are difficult to classify dueto the complexity of the human language.Evaluation also showed that the system can be more effective when domain specific,using the help of manual annotations to treat common exceptions. A system cantherefore combine multiple approaches with the intelligence of automatic algorithmsand manual annotations in order to provide a high degree of accuracy.

Many studies including this one is striving to discover patterns of use of language that can be reused, widespread and processed by computers. While many annotations are still required, they do not offer the necessary exibility and often turn out to be very specific domain. There are complex cases as the one presented during evaluation (which the system fails to correctly classify) which remains as challenges for new algorithms which are capable of solving disambiguation problems.

As discussed, when one is commenting about a product, a word can have different meanings or can refer to different objects. Solving this problem is a good challenge for new algorithms in Opinion Mining. Also, understanding the semantics of text in a more intelligent way is necessary. A good direction would be methods which have global knowledge of opinions dependent on complex contexts, which can use this information later to help solving context problems in any local analysis (at the sentence or word level).

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## BIOGRAPHY

**PallaPavankumar**is anAssistant professor in the Computer Science and Engineering Department,Keshav Memorial Institute of Technology, Narayanaguda, Hyderabad. He received Master of Technology (M.Tech) degree in 2012 from SKD college, Gooty, Ananatapur, India. His research interests are Data Mining, Computer Networks (wireless Networks), Image Processing, Algorithms etc.

**TippaniGayathri**is an Assistant professor in the Computer Science and Engineering Department,Keshav Memorial Institute of Technology, Narayanaguda, Hyderabad. She received Master of Technology (M.Tech) degree in 2014 from JNTU, Hyderabad India. Her research interests are Image Processing, Data Mining, Computer Networks (wireless Networks) etc.

**TippaniGayathri**is an Assistant professor in the Computer Science and Engineering Department,GeethanjaliInstitute of Science & Technology, Nellore. He received Master of Technology (M.Tech) degree in 2013 from JNTU, Anantapur, India. Her research interests are Image Processing, Data Mining, Computer Networks (wireless Networks) etc.