Ranking System for Opinion Mining of Features from Review Documents

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Abstract

With the exponential growth of the web there has been explosive increase in the user generated contents in the form of customer reviews, blogs, discussion forums, social networks etc. Most of the contents are stored in the form of unstructured or semi structured data from where distillation of knowledge is a challenging task. In this paper we propose a feature wise opinion mining system which first extracts features from user generated contents, then determines the intensity of the opinions by giving emphasis to the modifier of the words, which expresses opinions. It finds the numeric score of all the features using Senti-WordNet and then calculates the overall orientation of the feature to determine how intense the opinion is for both the positive and negative features. The positive and negative features are identified by extracting the associated modifiers and opinions. The summary is presented by specifying the features in descending order of importance.

Keywords: *Opinion mining, Sentiment analysis, Natural language processing, Text mining.*

1. Introduction

The World Wide Web has grown exponentially in recent years both in terms of size and diversity of the contents provided. It has contributed a very large amount of data termed as *user generated content*. These new contents include customer reviews, blogs, and discussion forums which expresses customer satisfaction/dissatisfaction on the product and its features explicitly. Most of the time the customer does not directly indicate the choice in a straight forward manner but does so in sentences which contain the actual reviews along with lines which are general in nature and has nothing to do about the product or opinion. Such sentences are challenging due to many reasons like, user not writing the features explicitly, writing incorrect sentences, omitting punctuation marks and writing grammatical incorrect language. As customer feedback influences other customer decisions about buying the product, these feedbacks have become an important source of information for businesses when developing marketing and segmenting the customer. The difficulty lies in the fact that majority of the customer reviews are very long and their numbers are also very high which makes the process of distillation of knowledge a very difficult task. Most of the times a user will read a *few reviews* and will try to make a decision about the product. The chances that a user will end up taking a biased decision about the product are not ruled out. Similarly, manufacturers want to read the reviews to identify what elements of a product affect sales most and what are the features the customer likes or dislikes so that the manufacture can target on those areas. More importantly, the large number of reviews makes it hard for product manufacturers or business to keep track of customer's opinions and sentiments on their products and services.

Recent work has shown that the majority of the work in opinion mining of reviews has been bimodal [11]. Reviews are generally allotted a very high rating or extremely low rating. In such a situation the numerical rating or star rating is not sufficient to highlight the inherent meaning of the review. In such a situation the user has to read the whole review so as to make an informed decision about the features that the user likes to know before deciding on the product. More importantly, some users would like to know the specific features which he or she wants to have in the product before buying the actual product. For example a user might want to but a camera having a *night vision mode* because the majority of the photography is done in the night, and therefore he will try to find a camera having this feature as a top most feature. Several sentiment analysis approaches have proposed to tackle this challenge up to some extent at some level of granularity. However, most of the classical sentiment analysis mapping the customer reviews into binary classes – positive or negative, fails to identify the product features liked or disliked by the customers or even if there are, they are not explicitly ranking the features both for positive and negative features.

In this paper, we present a ranking based opinion mining system which uses linguistic and semantic analysis of text to identify key information components from text documents. The information components are centered on both product features, and associated opinions, which are extracted using natural language processing techniques and co-occurrence-based analysis. Since only those features on which customers express their opinions are of interest, we define an information component as a triplet <$\mathcal{F}$, $\mathcal{M}$, $\mathcal{O}$> where, $\mathcal{F}$ and $\mathcal{O}$ represents product feature and opinion respectively. $\mathcal{M}$ is an optional component representing adverbs that act as modifier and used to intensify the opinion $\mathcal{O}$. $\mathcal{M}$ is also used to capture the negative opinions explicitly expressed in the review. The novelty of the system lies in mining associated modifiers with opinions. For example, consider following snippets of opinion sentences: (i) *the picture quality is good*; (ii) *the picture quality is almost good;* (iii) *the picture quality is exceptional.* In all these three sentences the opinion word is *good, almost good and exceptional* but the associated modifiers are different that express the degree of customer satisfaction on *picture quality*. Now our work is to first determine the feature words, secondly to compile the list of modifiers and thirdly to rank the opinion in the order of the adjective the user has wrote. For example the word *exceptional or excellent* expresses more satisfaction from the user than the words *average or good*. For each extracted feature, the list of opinions and associated modifiers are compiled and their polarity is established using numerical scores obtained through Senti-WordNet. We also compile all the synonyms of a particular word extracted by us and find their numerical scores and then generate a list of features in descending order of the ranking based on the intensity of comment by the users for a particular product. We also present a visualization technique that provides a feature-based summary of review documents in their order of importance.

The remaining paper is structured as follows. Section 2 presents a brief introduction to related work. Section 3 presents the architectural details of proposed rank based opinion mining system. The experimental setup and evaluation results are presented in section 4. Finally, section 5 concludes the paper with possible enhancements to the proposed system.

2. Related Works

The term *opinion mining* appears as a process of identifying and extracting a list of product features, and aggregating opinions about each of them from review documents. Research on opinion mining started with identifying opinion bearing words, e.g., *great*, *amazing*, *wonderful*, *bad*, *poor* etc. Many researchers have worked on mining such words and identifying their semantic orientations. In [6,7], a bootstrapping approach is proposed, which uses a small set of given seed opinion words to find their synonyms and antonyms in WordNet. The history of the phrase *sentiment analysis* parallels that of *opinion mining* in certain respects. A sizeable number of papers mentioning *sentiment analysis* focus on the specific application of classifying customer reviews as to their polarity – *positive* or *negative* [5,7]. Given a set of evaluative documents $\mathcal{D}$, it determines whether each document $d \in \mathcal{D}$ expresses a positive or negative opinion (or sentiment) on an object. For example, given a set of movie reviews, the system classifies them into positive reviews and negative reviews. This classification is said to be at the document level as it treats each document as the basic information unit. Apart from the document-level sentiment classification, researchers have also studied classification at the sentence-level, i.e., classifying each sentence as a subjective or objective sentence and/or as expressing a positive or negative opinion [7].

Although, classical sentiment classification attempts to assign the review documents either positive or negative class, it fails to find what the reviewer or opinion holder likes or dislikes. A positive document on an object does not mean that the opinion holder has positive opinions on all aspects or features of the object. Likewise, a negative document does not mean that the opinion holder dislikes everything about the object. In an evaluative document (e.g., *a product review*), the opinion holder typically writes both positive and negative aspects of the object, although the general sentiment on the object may be positive or negative. To obtain detailed aspects, feature-based opinion mining is proposed in literature [7,9,12,15]. In [15] we proposed a method for extraction of triplet from the review documents but the ranking of features based on importance was not incorporated. In [7], a supervised pattern mining method is proposed. In [9,12], an unsupervised method is used. A lexicon-based approach has been shown to perform quite well in [8,9]. The lexicon-based approach basically uses opinion words and phrases in a sentence to determine the orientation of an opinion on a feature. The classification approach of customer reviews based on existing domain-specific corpus by applying a lexicon based sentiment analysis has been discussed in [3]. Semantic analysis method has also been proposed in [16].

In [1] a support Vector Machine, supervised machine learning method has been used in order to classify reviews. They have compared the result obtained with different other work in order to find their feasibility. Weakness Finder has been proposed in [2], which crawls reviews from Internet for a well known cosmetic manufacturer to find their body wash weaknesses. It groups product features into corresponding aspects for Chinese reviews by applying semantic methods.

3. Proposed Opinion Mining System

The complete framework of the Opinion Mining of feature words is given in Fig.1. It consists of five major modules – *Document Processor, Subjectivity/Objectivity Analyzer, Document Parser, Feature and Opinion Learner, Review*

Summarizer & Ranker. The working principles of these components are explained in the following sub-sections.

3.1 Document Processor

This module is responsible for identifying relevant portion of a text documents. It consists of a Markup Language (ML) tag filter which divides the individual documents in individual record size chunks and presents them as individual unstructured record documents for further processing. The cleaned document is then converted into numeric-vectors using unigram model for the purpose of subjectivity/objectivity analysis. In document vectors a value represents the likelihood of each word being in a subjective or objective sentence.

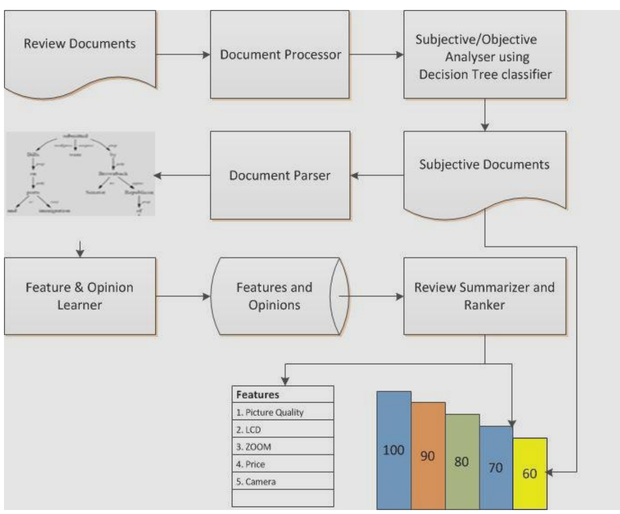

Fig. 1. Architecture of the proposed Opinion mining and Ranking system

3.2 Subjectivity/Objectivity Analyzer

According to Pang and Lee [13] subjective sentences are expressive of the reviewer's sentiment about the product, and objective sentences do not have any direct or obvious bearing on or support of that sentiment. Therefore, the idea of subjectivity analysis is used to retain segments (sentences) of a review that are more subjective in nature and filter out those that are more objective. This increases the system performance both in terms of *efficiency* and *accuracy*. The idea proposed by Yeh [12] is used to divide the reviews into subjective parts and objective parts. In [12], the idea of cohesiveness is used to indicate segments of a review that are more subjective in nature versus those that are more objective. We have used a corpus of subjective and objective sentences used in [13] for training purpose. The training set is used to get the probability for each word to be subjective or objective, and the probability of a sentence to be subjective or objective is calculated using the unigram model. The Decision Tree classifier of Weka is trained to classify the unseen review sentences into subjective and objective classes.

3.3 Document Parser

Since our aim is to extract product features and the opinions from text documents, all subjective sentences are parsed using Stanford Parser [1], which assigns Parts-Of-Speech (POS) tags to English words based on the context in which they appear. The POS information is used to locate different types of information of interest inside the text documents. For example, generally noun phrases correspond to product features, adjectives represent opinions, and adverbs are used as modifiers to represent the degree of opinion expressiveness. Since, it is observed that opinion words and product features are not independent of each other rather directly or indirectly inter-related through some semantic relations, each sentence is converted into dependency tree using Stanford Parser. The dependency tree, also known as word-word relationship, encodes the grammatical relations between every pair of words. A sample POS tagged sentence and the corresponding dependency tree generated using Stanford Parser is shown in figure 2(a) and 2(b) respectively.

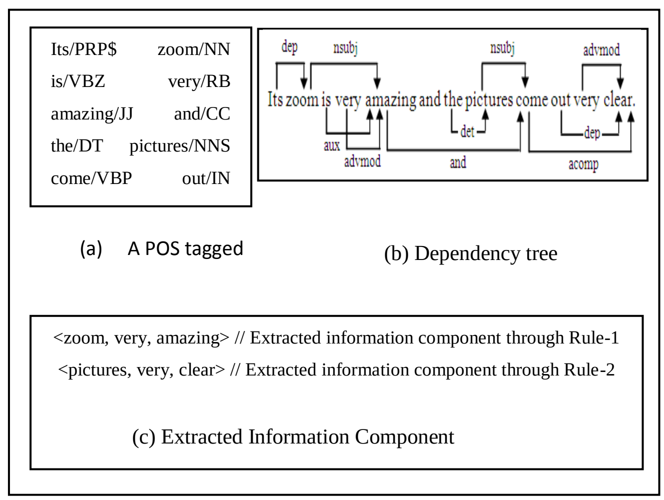

Fig. 2. (a) A POS-tagged sentence, (b) the corresponding dependency tree generated by Stanford Parser, and (c) extracted information components

3.4 Feature and Opinion Learner

This module is responsible to extract feasible information component from review documents. Later, information components are processed to identify product features and opinions. It takes the *dependency tree* generated by *Document Parser* as input and output the feasible

[1] http://nlp.stanford.edu/software/lex-parser.shtml

information component after analyzing noun phrases and the associated adjectives possibly preceded with adverbs. On observation, we found that product features are generally noun phrases and opinions are either only adjectives or adjectives preceded by adverbs. For example, consider the following review sentence:

- `ROOT(S(NP(NP (DT The) (NN battery) (NN life))(PP (IN of) (NP (NNP Nokia) (NNP N95))))(VP (VBZ is)(ADJP (RB very) (JJ good)))(. .)))`

In the above sentence, "battery life" is a noun phrase and appears as one of the features of Nokia N95 whereas, the adjective word "good" along with the adverb "very" is an opinion to express the concern of reviewer. Therefore, we have defined the information component as a triplet <$\mathcal{F}$, $\mathcal{M}$, $\mathcal{O}$> where, $\mathcal{F}$ is a noun phrase and $\mathcal{O}$ is adjective word possibly representing product feature. $\mathcal{M}$ represents adverb that act as modifier and used to intensify the opinion $\mathcal{O}$. $\mathcal{M}$ is also used to capture the negative opinions explicitly expressed in the review.

3.4.1 Information Component Extraction

The information component extraction mechanism is implemented as a rule-based system which analyzes dependency tree to extract information components. Some sample rules are presented below to highlight the function of the system.

Rule 1: In a dependency tree $\mathcal{T}$, if there exists a *subj*(w_i, w_j) relation such that POS(w_i) = JJ*, POS(w_j) = NN*, w_i and w_j are not stop-words[1] then w_j is assumed to be a *feature* and w_i as an *opinion*. Thereafter, the relation *advmod*(w_i, w_k) relating w_i with some adverbial words w_k is searched. In case of the presence of *advmod* relation, the information component identified as <w_j, w_k, w_i> otherwise <w_j, -, w_i>.

Rule 2: In a dependency tree $\mathcal{T}$, if there exists a *subj*(w_i, w_j) relation such that POS(w_i) = VB*, POS(w_j) = NN*, and w_j is not a stop-word then we search for *acomp*(w_i, w_m) relation. If *acomp* relation exists such that POS(w_m) = JJ* and w_m is not a stop-word then w_j is assumed to be a *feature* and w_m as an *opinion*. Thereafter, the modifier is searched and information component is generated in the same way as in rule 1.

Figure 2(c) presents two sample information components extracted by applying these rules on the dependency tree shown in figure 2(b). The algorithm, shown in table 1, presents the implementation details of this system.

Table 1: Information component extraction algorithm

Algorithm:

Information_Component_Extraction ($\mathcal{F}_T$)

```
Input: F_T - a forest of dependency trees
Output: L_IC - information components
L_IC ← φ
for each T ∈ F_T do
If ∃at least one relation subj(w_i, w_j) in T then
for each relation subj(w_i, w_j) ∈ T do
feature ← opinion ← modifier ← " " // null string
if POS(w_j) = NN* && w_j ∉ L_SW then // L_SW is a list of stop words
if POS(w_i) = JJ* then feature ← w_j; opinion ← w_i
if ∃advmod(w_i, w_m) ∈ T then modifier ← w_m
end if
L_IC ← L_IC ∪ {<feature, modifier, opinion>}
else if POS (w_i) = VB* then
if ∃a relation acomp(w_i, w_k) ∈ T then feature ← w_j; opinion ← w_k
if ∃advmod(w_j, w_m) ∈ T then modifier ← w_m
end if
L_IC ← L_IC ∪ {<feature, modifier, opinion>}
end if
end if
end if
end if
end for
else for each amod(w_i, w_j) ∈ T such that POS(w_i) = NN* && w_i ∉ L_SW do
if ∃a relation amod(w_i, w_k) or nn(w_i, w_k) ∈ T then
if POS(w_k) = VBG then feature ← w_k+ w_i; opinion ← w_j
else if POS(w_j)=RB* then feature←w_i; opinion←w_k; modifier←w_j
else feature ← w_i; opinion ← w_j; modifier ← ""
end if
else feature ← w_i; opinion ← w_j; modifier ← ""
if ∃advmod(w_j, w_m) ∈ T then modifier ← w_m
end if
end if
end if
L_IC ← L_IC ∪ {<feature, modifier, opinion>}
end for
end if
end for
return L_IC
```

3.4.2 Feature and Opinion Extraction

Though a large number of commonly occurring noun and adjective phrases are eliminated due to the design of the information component itself, it is found that further processing is necessary to consolidate the final list of information components and thereby the product features and opinions. During the consolidation process, we take care of two things. In the first stage, since product features are the key noun phrases on which opinions are applied, so a feasible collection of product features is identified using term frequency (*tf*) and inverse document frequency (*idf*). In the second stage of analysis, however, for each product feature the list of all opinions and modifiers is compiled

[1] A list of 571 stop-words available at http://www.aifb.uni-karlsruhe.de/WBS/aho/clustering

that are used later for polarity determination of the opinion sentences.

The *tf-idf* value for each noun phrase is calculated using equations 1 and 2 where, *tf(t_i)* is the number of documents containing t_i, |D| is the total number of documents and $\left|\left\{ d_j : t_i \in d_j \right\}\right|$ is the number of documents where t_i appears. All those noun phrases having *tf-idf* value above a threshold are considered as relevant features. Thereafter, for each retained feature, the list of opinion words and modifiers are compiled from information components and are stored in a structured form.

$$tf\text{-}idf(t_i) = tf(t_i) \times idf(t_i) \qquad (1)$$

$$idf(t_i) = \log\left(\frac{|D|}{\left|\left\{ d_j : t_i \in d_j \right\}\right|}\right) \qquad (2)$$

A partial list of product features, opinions, and modifiers extracted from a corpus[1] of 1125 customer reviews on *digital camera* shown in table 2.

Table 2: A partial list of extracted features, opinions and modifiers

Product	Feature	Modifier	Opinion
Digital Camera	picture	not, really, very	beautiful, clear, fantastic, good, great, professional, sharp
	battery	Very	decent, excellent, rechargeable
	Price	---	cheap, excellent, good, great
	Zoom	-	Good, great, excellent, small
	Picture quality	Very, really	Nice, Exceptional, awesome, great, good

3.5 Feature Visualizer and Ranker

The working principle of this module can be summarized as follows:

- Firstly, the polarity of extracted opinions for each feature are classified using Senti-WordNet [14], a lexical resource in which each WordNet synset *s* is associated to three numerical scores *Obj(s)*, *Pos(s)* and *Neg(s)*, describing how objective, positive, and negative the terms contained in the synset are. A partial list of opinions and their positive polarity values (shown in parenthesis) obtained through Senti-WordNet is beautiful (0.75), clear (0.5), fantastic (0.875), good (0.75), great (0.625).
- For each feature, the opinion sentences are examined and mapped into one of the *positive* or *negative* class based on the score value of the associated opinions obtained in the previous step. The *objective* class is not considered as most of the users are interested in either *positive* or *negative* views rather than *neutral* views. The *max* function is applied to decide the class of an opinion sentence. In case of presence of multiple features in an opinion sentence, the one having highest score value is used to decide its class.
- A table is maintained for all the features along with their positive opinion words with their positive polarity values and the number of sentences in which this feature appears. Similar table is maintained for negative features also but with negative polarity values.
- The overall weight of a feature is calculated by multiplying the polarity value of the opinion word with the number of sentences which contain that opinion. It is given by the following formula.

$$Total\ Wt = \sum_{n=1}^{d} (Wt\ of\ Positive\ features - Wt\ of\ negative\ features) \qquad (3)$$

where *d* is the number of documents which contain this feature along with a commented word. A sample calculation for generating the weight using equation 3 of some of the is as follows :

Wt_{LCD} =(1.0x317 + 0.875x56 + 0.75x38) – (0.375x4) = +393.0

Wt_{Zoom}=(1.0x65 +0.25x3 + 0.875x56) – (0.375x5 + 0.5x2) = +11.25

Wt_{Price}= - (0.25x56 +0.125x23) = -16.875

The cumulative weight gives the true picture because it is dependent on two things, number of users who are writing the reviews and the number of features commented by each user. The features after being identified as positive will be considered the top feature if the numeric score of that feature is highest among all positive features extracted and their cumulative weight calculated. If the total weight of a feature is positive then that feature is termed as positive and is thought to be liked by the user. Similarly a negative weight indicates the feature is not liked by the user and hence will be categorized in the negative feature category.

Two lists are maintained in the descending order of weights one for the positive features and the other for negative features. A partial list of the features extracted along with their overall weight is given in Table 6 and Table 7.

[1] Review documents were downloaded from http://catalog.ebay.com/

4. Experimental Results

In this section, we present the experimental details of the proposed opinion mining system. For subjectivity analysis, we used the subjectivity dataset [1] v1.0 from Cornell for training purpose. The dataset consists of 1000 subjective sentences and 1000 objective sentences. A Java program is written to extract features using unigram model from this dataset and to convert each sentence into equivalent numeric vector where a value represents likelihood of each word being in a subjective or objective sentence. Thereafter, the Decision Tree classifier of Weka is trained to classify the unseen sentences into subjective and objective classes. The accuracy of the classier on 10-fold cross validation is 82%. The data sample used in our work to mine features and opinions for customer reviews summarization consists of 1125 review documents on different models of digital camera which is having approximately the same cost – all obtained from www.ebay.com. The algorithm presented in table 1 was implemented using Java to mine features and opinionated words along with modifiers from the subjective review sentences. Initially, a total of 131 features for *digital camera* were extracted out of which only 22 were retained after feasibility analysis. For each retained feature, the list of both opinions and modifiers were compiled, a partial view of positive and negative features which have been shown in table 3 and table 4 respectively.

Table 3: Score value of positive features

Features	Opinion Word	Modifier	score	No. of sentences
LCD	Excellent		1.0	317
LCD	Good	Very	0.875	56
LCD	Good	-	0.75	38
Zoom	Excellent	-	1.0	65
Zoom	Exceptional	-	0.25	3
Zoom	Awesome	-	0.875	56
Picture	Excellent		1.0	457
Picture quality	Good		0.75	162

Table 4: Score value of negative features

Features	Opinion Word	Modifier	score	No. of sentences
Price	High	-	-0.25	56
Price	High	Little	-0.125	23
Battery Life	Short	-	-0.375	69
Picture	Blurry	-	-0.75	1
LCD	Small	-	-0.375	34
Zoom	Small	-	-0.375	5
Zoom	Average	-	-0.50	2

Since some opinion word contains the modifier also therefore while calculating the score value we upgrade or downgrade the score depending whether the commented feature is a positive or negative word. The upgrading is done by first finding the polarity value of that word without the modifier and then adding 0.125 in the case of upgrading and downgrading. Since the words in the negative list comes with a minus sign the value added will ultimately contribute to make the feature more negative since after adding the value with a negative sign will make it more negative. The value 0.125 has been taken because it has been found in Senti-WordNet that the difference in score values of word "*excellent*" and "*good*" is 0.25. Therefore it is assumed that very good will come between good and excellent, and hence the value of 0.125 is taken which is the average of the two scores.

4.1 Evaluation Methods

We now present a discussion on the performance of the whole system which is analyzed by taking into account the performance of the *feature and opinion* extraction process. Since terminology and complex proper names are not found in Dictionaries, an obvious problem of any automatic method for concept extraction is to provide objective performance evaluation. Therefore manual evaluation has been performed to judge the overall performance of the system. For evaluation of the experimental results, we use standard IR performance measures. From the extraction results, we calculate the true positive *TP* (number of correct feature-opinion pairs the system identifies as correct), the false positive *FP* (number of incorrect feature-opinion pairs the system falsely identifies as correct), true negative *TN* (number of incorrect feature-opinion pairs the system identifies as incorrect), and the false negatives *FN* (number of correct feature-opinion pairs the system fails to identify as correct). By using these values we calculate the following performance measures:

- **Precision (π):** the ratio of true positives among all retrieved instances.

$$\pi = \frac{TP}{TP + FP} \tag{4}$$

- **Recall (ρ):** the ratio of true positives among all positive instances.

$$\rho = \frac{TP}{TP + FN} \tag{5}$$

- **F1-measure (F_1):** the harmonic mean of recall and precision.

$$F_1 = \frac{2\rho\pi}{\rho + \pi} \tag{6}$$

[1] http://www.cs.cornell.edu/people/pabo/movie-review-data/

The values of the above performance measures are calculated for each category of experimental data. In order to present a synthetic measure of performance over all categories, we present the macro-averaged performance which consists in simply averaging the result obtained on each category.

Table5: Performance evaluation of the feature-opinion extraction process

Product Name		Precision (%)	Recall (%)	F1-measure (%)
Digital Camera	**Canon**	92.50	57.81	71.15
	Kodak	94.83	42.97	59.14
	Nikon	91.67	41.12	56.77
	Panasonic	91.43	64.00	75.29
Macro-average		92.61	51.48	65.59

Table 5 summarizes the performance measure values for our system in the form of a misclassification matrix. The recall value is lower than precision indicating that certain correct feature-opinion pairs could not be recognized by the system correctly. This is justified since most of the reviewers do not follow the grammatical rules while writing reviews due to which the parser fails to assign correct POS tag and thereby correct dependency relations between word pairs. However, most of the identified feature-concept pairs are correct, which leaves scope for enhancing our grammar to accommodate more dependency relations. After analyzing the review documents manually we also found that some review documents contain junk sentences too which opens a new direction of research on how to eliminate these spam review and improve the performance of the system.

Now we present a discussion on ranking of the features in descending order of the importance. We start will the weight of the features which was calculated and have given the values in Table 3 and Table 4. The final overall weight is calculated for all the features using equation 1. The weights of the few features calculated are shown below.

Weight of feature *LCD* = +394.5
Weight of feature *Zoom* = +11.25
Weight of feature *Price* = -16.875

Now our last task is to rank the features of a product in the order of importance. Since we have already calculated the polarity value of the features we arrange the features in the descending order of importance. Table 6 and Table 7 give the rank of a few features .

Table 6: Rank of the positive features for Camera(Top 5)

Rank	Features	Positive polarity values
1.	Picture	578.5
2.	LCD	393.0
3.	Zoom	11.25
4.	Lens	9.25
5.	Photos	7.0

Table 7: Rank of the negative features for Camera(Top 3)

Rank	**Features**	**Negative polarity values**
1.	Battery	-25.875
2.	Price	-16.875
3.	Size	-13.0

The experimental study showed that more number of features in negative list could not be extracted as most of the reviews written by the users were on the positive side and there were only 33 reviews which commented on the negative point on the feature *size*. *Battery* feature invited only 69 negative comments. The number of negative comments on *Price* was 79.

Fig 3 and 4 gives the graph of feature versus weight value by taking the overall weight of the features both for positive features and negative features.

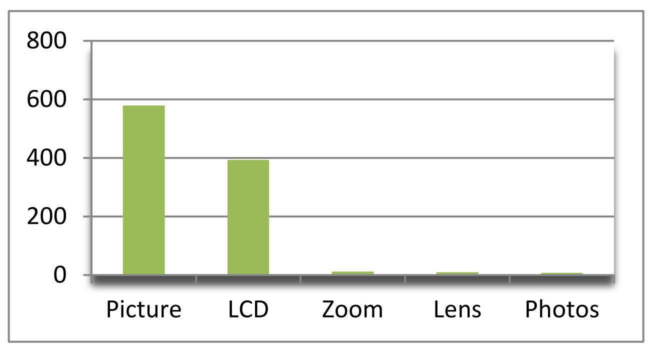

Fig 3: Graph of *Features* versus *Feature Weight* for positive features

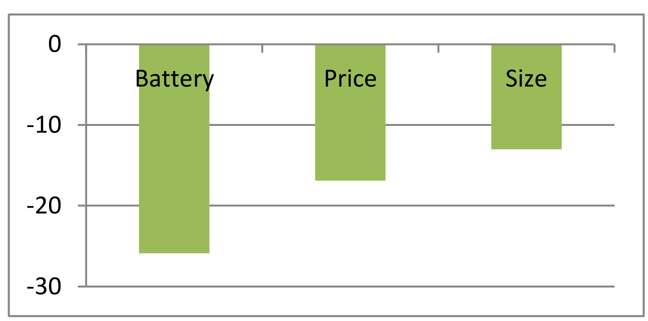

Fig 4: Graph of *Features* versus *Feature Weight* for negative features

5. Conclusions

In this paper we have proposed a rank based system for features from user generated contents for different models of camera. We firstly identified the features and their modifiers and then found there polarity values. Secondly we calculated the weight of each features and ranked them on the basis of their score values. We have also separated the positive and negative features so that the user and the manufacturer would know the features which are generally liked and disliked by the user. Manufacturer can accordingly develop business plans so that necessary improvement can be done in those areas. It is observed that the recall values of the system is low since a sizeable amount of reviewers did not use correct English and the parser fails to identify the sentence and does not give correct POS.

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