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Fuzzy Based Summarization of Product Reviews for Better Analysis

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Abstract

Background/Objectives: There is a tremendous growth in the online product's where customers buy a product and leave a comment on it about their experience. These experiences, which are in the form of reviews, help in two ways. **Methods/Statistical Analysis:** Firstly, the buyer will have a clear idea about the products pros and cons. Secondly; manufacturer will also find them helpful to make the user experience better by improving the product or service in negative areas. This user reviews at a point where, if the user reviews are thousands in number for a single product, we can propose a system, which provides the summary of all user generated reviews. This is what motivated opinion-mining systems to summarize the user reviews. Opinion mining is the current technology, which can classify the review documents to summarize them. **Findings:** This paper implements the opinion mining based on fuzzy logic to improve classification of reviews for generating the concise summary about the product. **Application/Improvements:** This is a Feature based sentiment classification which is a multistep process which involves pre-processing phase, fuzzy score to classify each review, training the Naive bayes classifier, evaluating each sentence in the test set depending on the trained classifier and ranking the sentences for each feature. Thus, sentences evaluated are a fine-grained classification to better summarize the reviews.

Keywords: Naive Bayes Classifier, Opinion Mining, Sentiment Analysis, Sentence Ranking

1. Introduction

It is apparent now a day that products are bought depending on the positive reviews they have which is why it's very important to consider what people reviewed about the product. Online product reviews thus, paved the way to make money for businesses to better understand customers and reinvent products gain a positive reputations[1,2]. Most importantly, we always think of taking a second opinion from our close friends about the product. In addition, Internet being freely available to everyone these days, people are more comfortable to check opinions in the internet prior to purchasing the product.

The internet giant in ecommerce Amazon.com is now making the datasets of reviews openly available for research purpose. In addition to these kinds of websites, even Google search engine is also being another important source for people to search for other people's opinions. Although this does not have the facility to identify polarity of the review which requires some natural language processing. Opinion Mining has seen light in the recent years. Earlier, reviews are classified as positive or negative like a binary classification problem, we propose a different way to classify the reviews in very positive and very negative including positive and negative. Given a review, the classifier tries to classify the review into positive category or negative, very positive, or very negative category. However, opinions in natural language are usually expressed in subtle and complex ways. Thus, a simple classification algorithm like k-means does not work great with this type of complex problems. In this paper, we collected mobile/hotel reviews from variety of e commerce websites. Sentiment analysis is performed to determine the semantic orientation of the reviews and movie-rating score is based on the sentiment-analysis result[3]. We designed the whole systems model in a way it can be applied to various domains like hotel, movie, and any other products. Our work lead us to a point where the opinion mining results can work as recommendation

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system just like the search engine answers, but this recommendation system when queried gives the result which includes the summarized opinion.

The main contributions of this paper are the following

- Modelled and developed a product/service review summarization system, which can be applied to any other irrespective of the domain.
- Designed a complete new architecture according to our approach to solve the problem of huge amount of review data. Product features and opinion words are used to select appropriate sentences to become a review summarization.
- Propose a novel approach to pick out the best sentences that describe the product/service taking into account few important parameters just like ranking the sentences.

2. Related Surveys

The opinion mining was started with the advent of technology that can differentiate between positive and negative words, which certainly are part of sentences and documents of reviews. Senti-word net is huge database, which contains every word's sentiment polarity as positive and negative form. Mita K. Dalal and Mukesh A. Zaveri, et al.,[1] proposed a system to summarize the reviews taking top 5 reviews. They used the fuzzy approach for computing polarity of the sentence and used Senti-word net for the word level polarity. Here we learned that opinion-mining system that can be used both binary and fine-grained sentiment classification of user reviews. Jung-yeon, Yang, et al. and K. Vithiya Ruba and D. Venkatesan[4,5] in their summarization approach; context-sensitive information is used to determine sentiment polarity while opinioned-feature frequency is used to determine feature scores. Based on experiments with actual review data, this method improved the accuracy of the calculated feature scores and outperformed existing methods. Maqbool Al-Maimani, Naomie Salim et al.,[6] presented a review covering the semantic and Fuzzy-based logic techniques and methods in sentiment analysis and challenges appear in the field. N.S. Ambekar, N.L. Bhale et al.,[7] proposed a new method i.e., fuzzy ontology tree for giving a more clear and precise analysis of sentiments to give best quality poll to customers. This approach allows the system to handle opinion words that are context dependent, which cause major difficulties for existing algorithms. In the reviews, a single sentence may exhibit multiple aspects for opinions. Bootstrapping algorithm is used to handle this problem. The proposed method does not require labelled data and hence easy to implement. Md. Ansarul Haque, Tamjid Rahman et al.,[8] proposed that, fuzzy logic could be introduced for more specification of the sentiment values. Therefore, sentiment analysis with the help of fuzzy logic (deals with reasoning and gives closer views to the exact sentiment values) will help the producers or consumers or any interested person for taking the effective decision according to their product or service interest. Raghava Rao Mukkamala, Abid Hussain and Ravi Vatrapu et al.,[9] proposed the computational approaches to social media analytics are largely limited to graph, theoretical approaches such as Social Network Analysis (SNA) informed by the social philosophical approach of relational sociology. There are no other unified modelling approaches to social data that integrate the conceptual, formal, software, analytical and empirical realms. Second, they outline a formal model based on fuzzy set theory and describe the operational semantics of the formal model with a real-world social data example from Facebook. Third, they briefly presented and discuss the Social Data Analytics Tool (SODATO) that realizes the conceptual model in software and provisions social data analysis based on the conceptual and formal models. Fourth, they use SODATO to fetch social data from the Facebook wall of a global brand, H&M and conduct a sentiment classification of the posts and comments. Fifth, they analyse the sentiment classifications by constructing crisp as well as the fuzzy sets of the artefacts (posts, comments, likes, and shares). Shaidah Jusoh and Hejab M. Alfawareh et al.,[10] focused on opinion mining research, to classify opinion into three categories; positive, neutral, and negative. Classifying opinion, which is presented in a phrase, remains a challenge to researchers in this area. This paper has introduced an approach for classifying opinion, which is presented in a phrase into two categories; positive and neutral. The approach is obtained by applying information extraction technique and fuzzy sets to the texts that contain opinion. Pranali Tumsare, Ashish S. Sambare et al.,[11] studied movie reviews using sentiment analysing approaches. In this study, sentiment classification techniques were applied to movie reviews. They determine the polarity of sentiments of the person in the review and comments when the sentences occur in documentary level. It uses Senti-wordnet dictionary to determine the scores of each word present in the comment. Sentiments of words are classified in three scores, positive, negative and objective. It uses rule base and fuzzy logic approach to give the output. P. Thamizharasi and R. Sathiyavath et al.,[12] analysed the feedback in online marketing websites and rating of a product.

3. Methodology

3.1 Data Sets

For the analysis purpose, we have collected three data sets from the internet blogs.

It was a direct extraction from various websites, which provide the user reviews for the product/service. Over 400 reviews are collected which includes reviews about Hotel services and Mobile. We particularly choose these, as they are diverse reviews, which cover product and service realms, and as these are the buzz-words in the E-commerce industry now a days as shown in Table 1.

Table 1. Example data set

Data sets	No. of reviews	Website
Mobile set	200	Amazon.in and Flipkart.com
Hotel set	200	Oyster.com

3.2 Initial Text Mining and Pre-Processing

The reviews are pre-processed primarily to make them noise free at the classification part as the review sentences may describe about two or more features which will be difficult to classify if the sentence has positivity and negativity associated[13]. So the features if two or more are present in a sentence are splitted in order to eliminate the above case[14]. And we also took into consideration that the reviews scraped from the websites will contain some spelling mistakes which will be serious issue if: Example: 'Gud' may mean nothing to the computer which if corrected does make some sense like positive or negative. Thus the pre-processing includes these steps to make review sentences noise-free along with Stemming[13] as it is the standard procedure to make the words cut short to make match with the features. Example: Camera's would be reduced to Camera by stemming; Camra would result in camera-0.9 and cam-0.2 by checking spelling mistakes. Thus, pre-processing steps generate sentences, which can be parsed automatically by the Textblob, and it is very easy to tokenize them and process for the semantic analysis. Where the Senti-word net database retrieves the word polarity as positive or negative only for the Nouns and Adjectives.

3.3 Feature Selection

Our system is designed to produce a summary of the product/service based on the features, which describe the product quality. Therefore, we employed a novel approach to extract right features from large number of features without considering unimportant features[15]. We selected top 5 features based on the word frequency in the reviews which best describe the product/service and used them to produce a genuine summary of the respective product as shown in Table 3[16].

3.4 Sentiment Polarity and Text Blob

After all the pre-processing tasks and the required features are set up each review sentence is processed to calculate the Polarity of the sentence associated with the feature. Senti-wordnet is a large database consisting of many words associated with its pos and neg score[17].

Example: 'Good' has a positivity score of 0.75 and negativity score of over 0.0.

Thus the sentences are first tokenized to check for the words which are adverbs/adjectives and nouns. Then we apply a POS tagging to select Adverbs/Adjectives and Nouns. Here adverbs/adjectives and nouns are only considered because the word which describes the feature in a review sentence is an adverb or a noun. Example: The body of the mobile is fragile. This sentence when tokenized and POS is applied will look like:

[(The,DT),(body,VBP),(of,IN),(the,DT),(mobile, NN), (is,VBZ),(fragile,JJ)]

Here we take the sentence to see if a feature is present in it or not to check if the sentence is worth further processing. If it does not have any feature, we continue with other review sentences.

3.5 Fuzzy Classification Phase

In this phase, we perform fine-grained classification of users' reviews. The reviews are classified as very positive, positive, neutral, negative, or very negative. We classify a new user review based on its fuzzy sentiment score whose computation requires three steps:

1. Identify the opinion words and the negator words if any 2. Identify the polarity and initial value of the feature descriptors based on Senti-wordnet score, and 3.

Calculate overall sentiment score using fuzzy functions to incorporate the effect of linguistic hedges.

The first two steps are performed as explained above. As discussed earlier, we consider the Senti-wordnet score of a feature descriptor as its initial fuzzy score $\mu(s)$.

If the descriptor has a preceding hedge, its modified fuzzy Score is calculated using

$f(\mu(s))=1-(1-\mu(s))^{\delta}$

Similar to Zadeh's proposition, if the hedge is a concentrator, we choose $\delta = 2$ which gives us modified fuzzy concentrator score[1], while if the hedge is a dilator we chose $\delta = \mathbf{1/2}$

Let us visit the smart phone's review sentence "The body is fragile". The initial sentiment score for the descriptor "fragile" obtained using Senti-word net is $\mu(s) = 0.625$. If this descriptor is preceded by a concentrator linguistic hedge, for example, "very fragile", then it's modified fuzzy score is obtained $f_c(\mu(s)) = 0.8593$. Similarly, if this descriptor is preceded by a dilator linguistic hedge, for example, "somewhat fragile", then its modified fuzzy score is obtained using as $f_d(\mu(s)) = 0.3876$. Thus, the intensity level of a descriptor is adjusted based on the linguistic hedge, whenever such hedges are present in a review sentence.

Now the value calculated will be multiplied by the -1 or +1 depending on the negator words the sentence consists. If the word 'not' is present the whole sentence will be negative so the score will be a negative. Thus this will result in sentence polarities in the range [-1,1].

We further normalize this value using min-max normalization to map it to the range [0,1]

ResScore = $(f(\mu(s))+1)/2$

If ResScore ≥ 0 and ResScore ≤ 0.25, then C = "very negative," Else

If ResScore >0.25 and ResScore <0.5, then C ="negative," Else

If ResScore>0.5 and ResScore ≤ 0.75, then C ="positive," Else

If ResScore>0.75 and ResScore ≤ 1, then C = "very positive."

This is the first hand procedure we implemented with our data set firstly. To brief about the algorithm we wrote, it first tokenizes and applies stemming. Now it searches for the opinion words and retrieves the score, but it produced results with low accuracy and the algorithm does take long time to return results. With advancement in python technology, we discovered a package, Textblob in python that does this procedure the same way and producing the results according to ResScore. *TextBlob* is a Python (2 and 3)[18] library for processing textual data. It provides a simple API for diving into common Natural Language Processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more. The Textblob has a class which takes the text reviews and returns a blob which contains the sentences splitted and formatted into a Sentence structure which when processed gives the polarity score within the range of [-1, 1]. Now we apply the min-max normalisation function to map it to [0, 1]. Now we assign a Class label vpos-very positive, vneg-very negative, pos-postive, neg-negative to each sentence based on the above states rules. Thus, a table is prepared with the training data set containing a sentence column and class label column shown in Table 2.

3.6 Naive Bayes Classifier

Naive bayes classification works with higher accuracy for text classification purposes as it works under the assumption of independence among the predicators. Without much explanation let's consider the following equation:

$$P(c|x)=P(x|c)P(c)/P(x) \tag{1}$$

Table 2. Assigned class labels for reviews

Sets	Sentence	Class label
Training Set	Great hospitality, Courteous staff.	pos
	Best rooms	vpos
	Excellent furnishing in the room.	vpos
	Very bad location.	vneg
	Excellent furnishing in the room.	vpos
	The staff was very courteous and cooperative.	vpos
	Not worth booking this hotel.	neg
	It was very nice, clean and well made.	vpos
Test set	Staff are amazing	?
	Worst hotel room ever	?

As applied the Naïve bayes (above discussed formula-1) the amazing word when tested for each class label i.e vpos,pos,vneg,neg gives the following results as shown:

- P(vpos | amazing)= P(amazing|verypos)* p(verypos)/P(amazing)= 0.212765*0.5164/0.109=0.999999999999999

- P(pos | amazing)= P(amazing|pos)* p(pos)/P(amazing)=0.33333*0.2967/0.109=0
- P(vneg | amazing)= P(amazing|vneg)* p(veryneg)/P(amazing)=0

As explained above, NBC classifier works by constructing a frequency table. It first tokenizes the words and forms the Table 3 where the words may be adjectives, nouns, or adverbs where the words best describe the sentence. The frequency table will be more complex when there are a lot more parameters other than just adjectives. After the frequency table is constructed, probabilities are computed for each row according to the bayes formula. As shown in the above results, the word 'amazing' is now computed with three class labels. 'Vpos' class label has the only amazing word and 'vpos' is given high probability. When 'pos' is checked, there is no word amazing in the pos column in the frequency table, so the entire numerator part will be 0 which in turn makes the whole value to be 0. Same follows for the other class labels also.

Table 3. World frequency

WORD	P	VP	N	VN
AMAZING	--	10	--	--
WORST	--	--	2	---
NICE	4	--	---	---
GOOD	15	---	----	----
VERY GOOD	---	5	----	----
SUPER	---	3	----	----
TOO BAD	----	---	23	22
GREAT	---	9	---	---
AWESOME	----	6	---	---
VERY BAD	---	---	---	4
EXCELLENT	---	2	---	---
VERY NICE	---	7	---	---

4. Test Set and Sentence Ranking Algorithm

We now take the Test set data we prepared to summarize the reviews in the test set. This makes the process of summarizing any product/service reviews easy as the computation time of sentiment polarity calculation is now eliminated and the classifier is trained enough to serve the purpose of better & concise review generation. After the classifier is given the test set the data classified as very positive, very negative, positive, negative are divided among four files and are kept as a back-up data. Now the task is to divide the test set among five features we selected before. The review sentences are divided into five different files based on different features. This is done solely to summarize the reviews based on the features. Now the primary consideration is which sentences to be picked to summarize the feature of product. We considered various parameters to rank the sentences so that best sentences, which describe product, will be extracted to present to the user. In our work to rank sentences, we learnt about following major aspects to consider:

- Subjectivity: Subjectivity is all about assigning a score greater than 0.75 if the sentence is too assertive and contains nouns that describe about product along with adjectives & without many stop words in the sentence. Thus, this helps in assigning more weight to the sentence[19,20].
- Sentiment polarity: The ResScore, which is calculated before, was also considered as a variable factor, which helps in eliminating the two sentences having the same overall rank at the end. Its use is not much significant but we considered it useful parameter as sentence polarity also affects the weight to the sentences.
- Positive and Negative frequency: In our work to rank the sentences, we considered to present user genuine summary of the product/service. Thus, we employed a novel approach to extract the reviews, which are at most important. Here we worked on proposing a formula:

Rank=Subjectivity + Sentiment polarity + Δ

Δ = (total positive or negative reviews)^2/total reviews

On the numerator part, if the current sentence is positive, it considers total positive reviews present for that feature and it squares to increase the probability of that sentence being in the summary and dividing it with the total reviews[2]. If the sentence is negative, we take total negative reviews count of that feature and divide it with total reviews. This part of the formula is a constant but changes only for negative and positive.

The major effect to ranking comes with the subjectivity and polarity of the sentence. The overall architecture as shown in Figure 1.

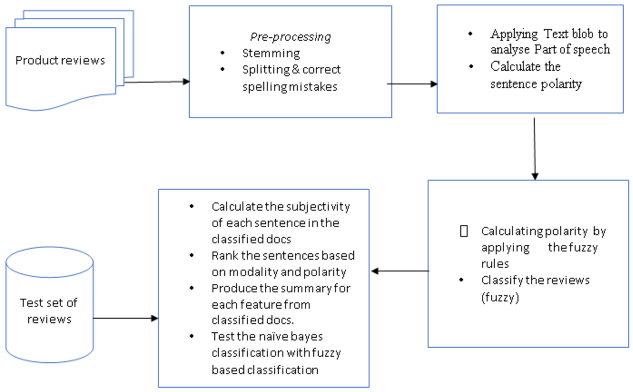


Figure 1. Architecture of product summarization.

5. Experimental Analysis

We tested our system with two data sets we collected from internet i.e., Mobile and Hotel data sets. From the architecture above, following tables shows the output for each module of the architecture.

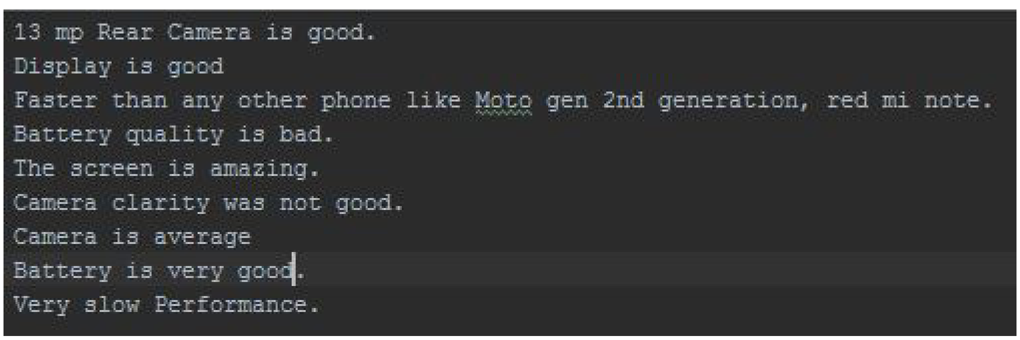
Table 4 shows the subset of dataset without noise removal and without pre-processing. We fed this data set into the software for pre-processing.

Table 4. Mobile dataset-subset

13 mp Rear Camera is good.
Display is goooood.
Faster than any other phone like Moto gen 2nd generation, red mi note.
Battery quality is bad.
The screen is amazing.
Camera clarity was not good.
Camera is average and battery is very good.
Very slw Performance.

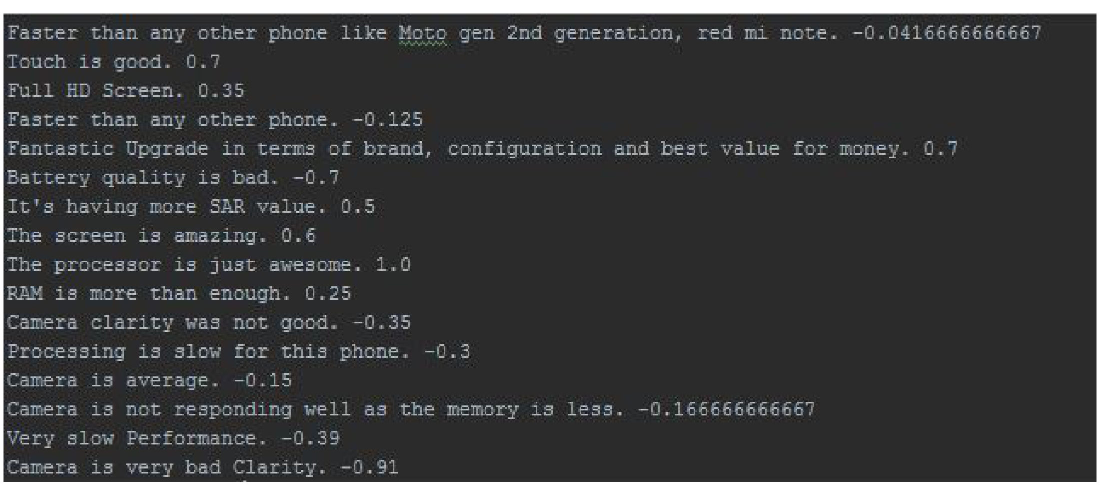
After the pre-processing is done, subset of data shown in Table 4 is converted into the following text shown in Figure 2.

This text is applied to a Textblob to compute the Sentiment polarity. The Textblob takes the text data and returns the sentences and their associated polarities through a blob. Usually the Sentiment polarity falls in the range [-1,1]. The following output depicts the same shown in Figure 3.



```
13 mp Rear Camera is good.
Display is good
Faster than any other phone like Moto gen 2nd generation, red mi note.
Battery quality is bad.
The screen is amazing.
Camera clarity was not good.
Camera is average
Battery is very good.
Very slow Performance.
```

Figure 2. After pre-processing phase.



```
Faster than any other phone like Moto gen 2nd generation, red mi note. -0.0416666666667
Touch is good. 0.7
Full HD Screen. 0.35
Faster than any other phone. -0.125
Fantastic Upgrade in terms of brand, configuration and best value for money. 0.7
Battery quality is bad. -0.7
It's having more SAR value. 0.5
The screen is amazing. 0.6
The processor is just awesome. 1.0
RAM is more than enough. 0.25
Camera clarity was not good. -0.35
Processing is slow for this phone. -0.3
Camera is average. -0.15
Camera is not responding well as the memory is less. -0.166666666667
Very slow Performance. -0.39
Camera is very bad Clarity. -0.91
```

Figure 3. Sentiment polarity.

Now we apply the fuzzy membership function to scale the values in range [-1,1] to a range of [0,1] using Linear member ship function. The output now will look like;

Now after training the Naive bayes classifier, the test set is fed to system for classification. The output produced by naive bayes is shown in Figure 5.

The output consists of the sentence or review and the class label, which is assigned to the review by the Naive bayes classifier. Vpos-verypositive and pos-positive, Vneg-very negative, neg-negative.

Now the Summary is to be produced using proposed functions. We take the top 5 reviews which are weighted according to the sentence stop words, modality and subjectivity. After considering required parameters to rank sentences, the output is shown in Figure 6.

The overall output producing the summary of the mobile data set after all the stages of processing is like: Camera is the top feature from the dataset and the top 5 reviews i.e., Camera, Battery, Weight of the phone, SAR Value and Touch ability given by user for the camera as shown in Table 5.

In Table 5 we took over 1000 reviews from various blogs. After training the Naive bayes classifier with the train data set, 30% of the train data set is checked to see

```
Faster than any other phone like Moto gen 2nd generation, red mi note. 0.479166666667
Touch is good. 0.85
Full HD Screen. 0.675
Faster than any other phone. 0.4375
Fantastic Upgrade in terms of brand, configuration and best value for money. 0.85
Battery quality is bad. 0.15
It's having more SAR value. 0.75
The screen is amazing. 0.8
The processor is just awesome. 1.0
RAM is more than enough. 0.625
Camera clarity was not good. 0.325
Processing is slow for this phone. 0.35
Camera is average. 0.425
Camera is not responding well as the memory is less. 0.416666666667
Very slow Performance. 0.305
Camera is very bad Clarity. 0.045
bad Battery back up. 0.325
```

Figure 4. Fuzzy results.

```
According to my view this phone is good in it's Look and all. vpos
The camera is really very good. vpos
Camera is working very good. vpos
Extreme super camera quality. vpos
Camera is very good. vpos
Camera is just awesome. vpos
I can't express how good the camera is. vpos
It was really great camera. pos
Touch is very bad at the edges. vpos
The phone is amazingly Light weight. vpos
Battery getting low without even using phone. neg
Processing is slow for this phone. neg
Display is just awesome. vpos
Back Camera is average. vpos
SAR value is very very high so it produces more radiation and affect health. vpos
Health is effected much because it has High SAR value. vpos
Camera is not responding well as the memory is less. neg
Very slow Performance. vpos
It is like feather weight. vpos
It's    looks are pretty. vpos
```

Figure 5. Naive bayes results.

```
The camera is really very good.\n11.575909090909093
Camera is working very good.\n11.825909090909093
Extreme super camera quality.\n11.476325757575757
Camera is very good.\n11.825909090909093
Camera is just awesome.\n12.090909090909092
I can't express how good the camera is.\n10.540909090909093
It was really great camera.\n11.490909090909092
Back Camera is average.\n10.753409090909091
Camera is not responding well as the memory is less.\n1.5742424242424242
single star for Camera and Hanging problem.\n10.76948051948052
13 mp Rear Camera is good but 5 mp Front Camera is average.\n10.978409090909091
```

Figure 6. Sentence ranking results.

Table 5. Summary of top five features of mobile data set

Camera	Battery	Weight of the Phone	SAR Value	Touch ability
Camera is just awesome.	Battery getting low without even using phone.	The phone is amazingly light weight.	SAR value is too high	Touch is very good.
Camera is working great.	Bad Battery backup.	It is feather like weight	SAR is high, radiation effects are worst.	Touch, I'm loving it.
Camera clarity is perfect.	Battery is not working fine, fix it.	Weight of this phone is adorable.	SAR is worst.	Touch is getting slower.
The camera is really very good	Battery quality is bad.	I am comfortable with its weight.		Touch is not too good.
It was great camera.	Battery is draining out fast, very poor.	Best phone, weight is just amazing.		Touch is very bad.

Table 6. Accuracy table

Data sets	Accuracy	Precision	Recall	F-score
Hotel Data set	0.885185185185	0.8653846153846154	0.9	0.9278350515463918
Mobile Data set	0.84623655914	0.9583333333333334	0.8214285714285714	0.8846153846153847

if the classifier is accurate in predicting the class label. The results are tabulated for the two data sets as shown in Table 6.

We also computed confusion matrix[21] to determine the accuracy rate:

Table 7. Mobile data set-confusion matrix

	Predicted neg	Predicted pos	Predicted verypos	Predicted veryneg
Actual neg	89	0	0	0
Actual pos	0	47	0	0
Actual verypos	9	0	20	10
Actual veryneg	0	0	0	25

Table 8. Hotel data set-confusion matrix

	Predicted neg	Predicted pos	Predicted verypos	Predicted veryneg
Actual neg	60	0	7	0
Actual pos	0	45	7	0
Actual verypos	0	0	42	1
Actual veryneg	0	0	3	49

6. Conclusion

We converted a huge amount of review data base which is difficult to read and decide for the customers into a feature based summary to make it better for users to know about the product and also for manufacturers to correct the product. We performed a moderate pre-processing and using naïve bayes approach we proposed better approach to solve the problem of enormous reviews about the products. From the, above results it is shown that the proposed opinion mining system performs both binary and fine grained sentiment classifications of user reviews with high accuracy. The proposed functions for fuzzy linguistic hedges and sentence ranking functions could be successfully incorporated into the sentiment classification tasks and for weighting the important sentences respectively.

In future, the proposed system may pave path to recommend the users with appropriate service or product based on the analysis we perform through this system. There by human interruption with this system is lessened every time for summary sake and improves the quality of the product. This also can be incorporated into a mobile through an app, which does save lots of time for the users searching about product. Future works for mobile framework for this system does have some scope to develop.

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