IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

PHONE RECOMMENDER: SENTIMENT ANALYSIS OF PHONE REVIEWS

Devendra Kamalapurkar [*1]**, Ninad Bagwe** [2]**, R. Harikrishnan** [3]**, Salil Shahane** [4]**,**
Mrs. Manisha Gahirwal [5]

[*1234] Department of Computer Engineering, VES Institute of Technology, Mumbai-400074, India
[5] Assistant Professor, Department of Computer Engineering, VES Institute of Technology, Mumbai-400074, India

ABSTRACT

Due to the increase in demand for e-commerce with people preferring online purchasing of goods and products, there is vast amount information being shared. The e-commerce websites are loaded with large volume of data. Also, social media helps a great deal in sharing of this information. This has greatly influenced consumer habits all over the world. Due to the vivid reviews provided by the customers, there is a feedback environment being developed for helping customers buy the right product and guiding companies to enhance the features of product suiting consumer's demand. The only disadvantage of availability of this huge volume of data is its diversity and its structural non-uniformity. The customer finds it difficult to precisely find the review for a particular feature of a product that s/he intends to buy. Also, there is a mixture of positive and negative reviews thereby making it difficult for customer to find a cogent response. Also these reviews suffer from spammed reviews from unauthenticated users. So to avoid this confusion and make this review system more transparent and user friendly we propose a technique to extract feature based opinion from a diverse pool of reviews and processing it further to segregate it with respect to the aspects of the product and further classifying it into positive and negative reviews using machine learning based approach.

KEYWORDS: aspect; sentiment analysis; feature extraction; machine learning

INTRODUCTION

In the recent years E-Commerce has exploded everywhere in the world, and majority of the population prefers to buy products through these websites. Consequently large amount of data in the form of reviews is produced which helps prospective buyers to choose the right product. Furthermore these reviews contain opinionated contents which can be useful for the company to identify the areas which need to be enhanced.
However it is impractical for the user to read each and every review about the product. Moreover, reading only few reviews may present a biased idea about the product. It is quite possible that some of the reviews lack credible sources, which the users have no means to differentiate. Besides the reviews and ratings provided do little to assess the specific features of the product. Due to all the above constraints, the user is unable to make a fully informed decision about the product.

Opinion mining also known as sentiment analysis can be used to extract customer reviews from different sources on the internet. This technique implements various algorithms to analyze the corpus of data and make sense out of it. This technique helps to identify the orientation of a sentence thereby recognising the element of positivity or negativity in it. Automated opinion mining can be implemented through a machine learning based approach. Opinion mining uses natural language processing to extract the subjective information from the data (in this case its customer reviews).

Opinion mining techniques can be applied to wide range of data. It can track the popular viewpoint or attitude of the general public towards a particular thing, person or an event. There are three general levels for opinion mining tasks: document level, sentence level and phrase level in Liu[1]. Document level tasks mainly help in

segregating the overall document into either subjective document or objective document. Further it can be distinguished into positive, negative or neutral. It can also help separate the spam from the non spam. The sentence level opinion mining is performed on the sentences which can help group certain sentences to summarise the opinion and also it can help identify comparative sentences to rank them accordingly. Phrase level deals with the aspects and is known as aspect based opinion mining. This helps to identify the reviewers' sentiment about specific aspects of the product. This level does the finer-grained analysis of the opinions.

RELATED WORKS

Product review sentiment analysis, also called as opinion mining, is a method of ascertaining the customers' sentiment about a product on the basis of their reviews. Liu [1] classifies the opinion mining tasks into three levels: document level, sentence level and phrase level.

Opinion can be represented as an entity consisting of five parameters: target entity, aspect in opinion, opinion holder, time when opinion is expressed, and the sentiment orientation of the opinion holder of a feature entity at a particular time. [2] Makes use of frequency itemset mining which by employing a certain minimum support count finds the itemsets. Further it makes use of Naive Bayesian algorithm for aspect and sentence orientations by using supervised term counting.

The opinionated reviews also contain other information that can be used to ascertain the sentiment about a product. Venkata Rajeev P et al [3] uses the reviews from flipkart.com and proposes the combination of four parameters: star ratings of the product, the polarity of the review, age of review and helpfulness score, for determining the opinion of a product.

The task of mining the features is of particular importance and many methods are suggested for it. Weishu Hu et al. [4] divide the opinion analysis tasks into three steps: identifying the opinion sentences and their polarity, mining the features that are commented upon by customers, and removing incorrect features.

The primary focus of product review system is identifying the adjective word in a sentence and identifying the sentiment behind it. Yan Luo et al. [5] suggests the final sentiment score of the review to be the cumulative sentiment score of all the adjectives in that review

D V Nagarjuna Devi et al. **[6]** proposes a system that uses a supervised classification approach called as support vector machine. This paper claims that the proposed classifier approach gives out the best result. It also identifies various challenges in sentiment analysis like sarcasm and conditional sentences, grammatical errors, spam detection and anaphora resolution. Sentence level classification is done on input data which is further classified according to the subjectivity/objectivity. Further aspect extraction is done using SentiWordNet. This is then further fed to SVM classifier to find the overall opinion.

Shoiab Ahmed et al. [7] proposes that the count of scored opinion words be classified into seven possible categories i.e. strong-positive, positive, weak-positive, neutral, weak-negative, negative, strong-negative. Sentiment analysis is then done with the help of these score counts.

PROBLEM DEFINITION

An application that collects reviews from the users about a certain product and analyses them. It would segregate the reviews into positive and negative reviews. The negative reviews will be helpful to the companies to further enhance their product based on the user's' feedback. The application further provides the pros and cons of the individual feature of the product. The application will further provide reports about the sentiment analysis performed on the products. We further aim to create a recommendation system that recommends products to users according to the feature requirement of user.

METHODOLOGY USED

The objective is to classify cell phone reviews according to their various aspects (or features, like camera, battery and sound). This is done by first scraping the required reviews from the Amazon US website, training a classifier to tag each review, running the scraped reviews through the trained classifier and finally presenting the results through a user interface.

The web crawler is written in the Python programming language, using the BeautifulSoup library. It visits the reviews page of each cell phone and sends an HTTP GET request to obtain the HTML code that would be displayed on a regular browser. The library is then used to create a parse tree from the HTML which is traversed. The HTML elements that store the required review data such as title, author, body, date and rating are identified and the data is copied and stored.

In order to train the classifier, the Stanford CoreNLP library is used. It provides an implementation of a Recursive Neural Tensor Network (RNTN) which is a very accurate Natural Language Processing algorithm. RNTNs have a tree structure with a neural net at each node. To analyze text with neural nets, words are represented as continuous vectors of parameters. Those word vectors contain information not only about the word in question, but about surrounding words; i.e. the word's context, usage and other semantic information. Meanwhile, the natural-language-processing pipeline will ingest sentences, tokenize them, and tag the tokens as parts of speech.

To organize sentences, recursive neural tensor networks use constituency parsing, which groups words into larger subphrases within the sentence; e.g. the noun phrase (NP) and the verb phrase (VP). This process relies on machine learning, and allows for additional linguistic observations to be made about those words and phrases. By parsing the sentences, they are structuring them as trees.The trees are later binarized, which makes the math more convenient. Binarizing a tree means making sure each parent node has two child leaves. Sentence trees have their a root at the top and leaves at the bottom, a top-down structure that looks like this:
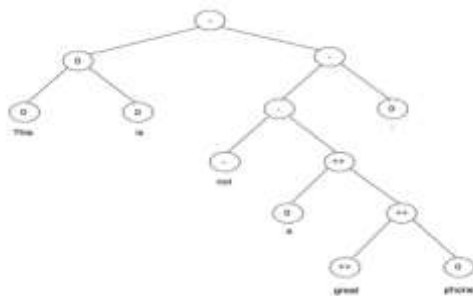
The entire sentence is at the root of the tree (at the top); each individual word is a leaf (at the bottom). The training data is in a similar format called the Penn TreeBank (PTB) format and is fed to the classifier to obtain the training model. This model is responsible for identifying the features present in the review and assigning a sentiment to it. The sentiment values can range from 0 - 4, 0 being the most negative and 4 being the most positive.

The scraped reviews are run through the classifier to obtain the aspect / feature ratings. The average of these ratings is taken as the feature rating for the phone. The web UI is written using Bootstrap for the front end and Django (a Python framework) for the backend. The aspecwise ratings for each review and phone are shown, which makes it easy for users to pick a phone according the the features they require.
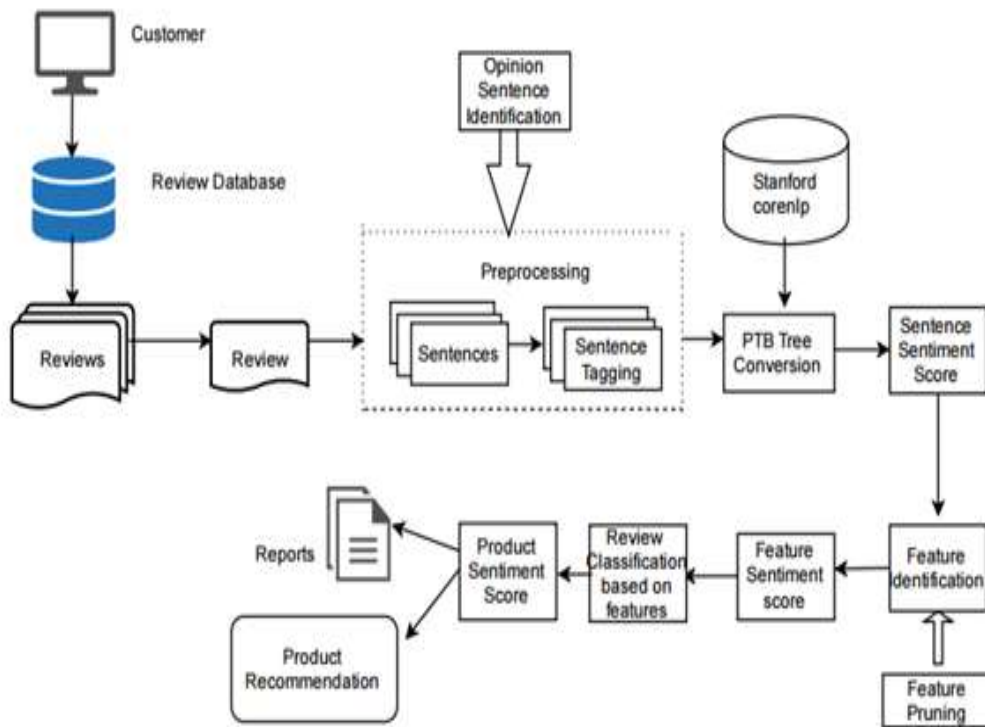
System Design

RESULT

Confusion matrix - A confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm. Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class (or vice versa).

Precision - Precision (also called positive predictive value) is the fraction of retrieved instances that are relevant. High precision means that an algorithm returned substantially more relevant results than irrelevant ones.

$$\text{Precision} = \frac{tp}{tp + fp}$$

Recall - Recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. High recall means that an algorithm returned most of the relevant results.

$$\text{Recall} = \frac{tp}{tp + fn}$$

Specificity - Specificity (also called the true negative rate) measures the proportion of negatives that are correctly identified as such.

$$\text{specificity} = \frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false positives}}$$

F1 score - The F-score can be used as a single measure of performance of the test for the positive class. The F-score is the harmonic mean of precision and recall.

$$F = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Label Confusion matrix

Predicted Actual	1	2	3	4	5
1	5	75	16	4	0
2	0	19	8	0	0
3	1	19	119	2	0
4	0	27	19	7	1
5	1	46	0	119	12

Predicted Actual	NEGATIVE	NEUTRAL	POSITIVE
NEGATIVE	56	12	2
NEUTRAL	16	70	1
POSITIVE	52	13	78

	NEGATIVE	NEUTRAL	POSITIVE
PRECISION	45.16%	73.68%	96%
RECALL/SENSITIVITY	80%	80.46%	54.54%
SPECIFICITY	68.5%	84.28%	97.67%
F - MEASURE	57.13%	76.95%	69.56%
ACCURACY	71.33%	82.92%	75%

CONSTRAINTS

Every system has some shortcomings or in other words all the system round the world work under some predefined constraints. Our system basically has 4 constraint under which it works.

1. Sarcasm:

It is an extremely difficult task for a machine to perceive a sarcastic review about any product and understand exact meaning of the review. It is even sometimes difficult for humans to interpret some of these sarcastic comments.

2. Errors in Grammar:

Due to social media apps people often commit grammatical mistake, punctuation errors and spelling mistake. In most of the cases in order to express their feelings about the product people deliberately type wrong spellings. This makes it difficult for the machine to figure out the exact meaning behind the review of a customer.

3. Detecting spam:

In this competitive world some users' usually try to post the negative reviews to spoil others' reputation. So it becomes extremely difficult rather impossible to segregate negative reviews from spam. Most of the time such reviews are considered as negative reviews by the machine.

4. Anaphora Resolution

In our product review system we focus on nouns that occur in a sentence and see whether that noun is a feature of that product or not using our feature database. But many times customer uses pronoun instead of the proper feature name to express his feeling about the product but in such case due to the absence of the feature name in that product the system fails to recognize it as an opinion sentence about a feature.

CONCLUSION

Our system processes the reviews of particular cell phone and on the basis of the reviews assigns a score to the phone as well as its features that reflects the user's sentiment. We have created a dashboard that displays all the popular phones and also their respective sentiment scores. In the phone's description view we provide the general information of the phone and also provide the list of reviews with corresponding sentiment score for the phone as well as for a particular aspect of the phone. To know more about the different aspects of a particular phone like camera, sound, battery, etc. proves to be helpful. Moreover since we analyze the reviews, the system generates a popular opinion about the phone, which in turn can be useful for the manufacturing companies. The system also provides phone recommendation functionality, where in a user can enter his expected phone specification, and the system provides the user with a list of alternatives, accompanied by the people's sentiment rating for the phone. Thus an amateur user gets the popular opinion from the user reviews and can make an informed decision while purchasing the phone.

REFERENCES

1. Bing Liu (2012), 'Sentiment Analysis and Opinion Mining', Synthesis Lectures on Human Language Technologies, Morgan & Claypool Publishers
2. A.Jeyapriya, C.S.Kanimozhi Selvi, "Extracting Aspects and Mining Opinions in Product Reviews using Supervised Learning Algorithm", 2nd International Conference On Electronics and Communication Systems(ICECS '2015)
3. Venkata Rajeev P, Smrithi Rekha V, "Recommending Products to Customers using Opinion Mining of Online Product Reviews and Features", 2015 International Conference on Circuit, Power and Computing Technologies [ICCPCT]
4. Weishu Hu, Zhiguo Gong, Jingzhi Guo, "Mining Product Features from Online Reviews", IEEE International Conference on E-Business Engineering
5. Yan Luo,Wei Huang, "Product Review Information Extraction Based on Adjective Opinion Words", 2011 Fourth International Joint Conference on Computational Sciences and Optimization
6. D V Nagarjuna Devi, Chinta Kishore Kumar,Siriki Prasad, "A Feature Based Approach for Sentiment Analysis by Using Support Vector Machine", 2016 IEEE 6th International Conference on Advanced Computing
7. Shoiab Ahmed, Ajit Danti, "A Novel Approach for Sentiment Analysis and Opinion Mining based on SentiWordNet using Web Data", 2015 International Conference on Trends in Automation, Communications and Computing Technology (I-TACT-15)
8. Python (programming language) - https://en.wikipedia.org/wiki/Python_(programming_language)
9. "Stanford Core NLP Toolkit" Available: http://nlp.stanford.edu/pubs/StanfordCoreNlp2014.pdf
10. Inferring networks of substitutable and complementary products J. McAuley, R. Pandey, J. Leskovec Knowledge Discovery and Data Mining, 2015

CITE AN ARTICLE: