Volume 8, No. 7, July – August 2017



International Journal of Advanced Research in Computer Science

# **RESEARCH PAPER**

# Available Online at www.ijarcs.info

# RESEARCH PAPER ON SENTIMENTAL ANALYSIS OF ONLINE CUSTOMER REVIEWS AND RATING

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*Abstract:* Sentiment Analysis is the process of determining whether a part of writing is positive, negative or neutral. It is also known as opinion mining or emotion AI (Artificial Intelligence) and refers to the use of natural language processing, text analysis, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. It is widely applied to voice of the customer materials such as reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine. In order to determine the sentiment of the overall document, we can use our own scoring algorithms – using the weighted phrases from the previous side, and then using our proprietary way of adding them up. By taking a set of content we can build a document-level sentiment classifier on it. In this thesis we are going to see how frequent item set can be used for mining reviews from online reviews posted by the customers. Our main aim is to create a system for analyzing sentiments or opinions which implies judgment of different consumer products.

Keywords: Sentimental Analysis, Opinion Mining, Frequent Words, Online Reviews, Rating.

# 1. INTRODUCTION

Sentiment analysis means to classify the polarity of a given text at the document level, sentence level, or feature/aspect level whether the expressed opinion in a document, a sentence or an entity feature/aspect is positive, negative, or neutral.

In Advanced Sentimental analysis we look beyond polarity classification, for instance, at emotional states such as angry, sad, and happy.

A different method for determining sentiment is the use of a scaling system whereby words commonly associated with having a negative, neutral, or positive sentiment with them are given an associated number simply from 0 to a positive upper limit such as +4 [1]. This makes it possible to adjust the sentiment of a given term relative to the level of the sentence.

When a piece of unstructured text is analyzed using natural language processing, each concept in the specified environment is given a score based on the way sentiment words relate to the concept and its associated score[9].

The rise of social media such as blogs and social networks has fuelled interest in sentiment analysis [10,11]. With the proliferation of reviews, ratings, recommendations and other forms of online expression, online opinion has turned into a kind of virtual currency for businesses looking to market their products, identify new opportunities and manage their reputations.

As businesses look to automate the process of filtering out the noise, understanding the conversations[13,14], identifying the relevant content and auctioning it appropriately, many are now looking to the field of sentiment analysis. One step towards this aim is accomplished in research.

Several research teams in universities around the world currently focus on understanding the dynamics of sentiment in e-communities through sentiment analysis. Even though short text strings might be a problem, sentiment analysis within micro-blogging has shown that Twitter can be seen as a valid online indicator of political sentiment [2].

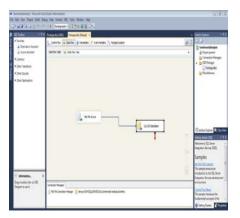
This paper is structured as follows. Section II describes the research methodology used in this study. Section III gives the steps in Sentimental Analysis. Section IV gives the classification of Sentimental Analysis. Section V presents the resulting reports. Section VI presents the conclusion and future directions.

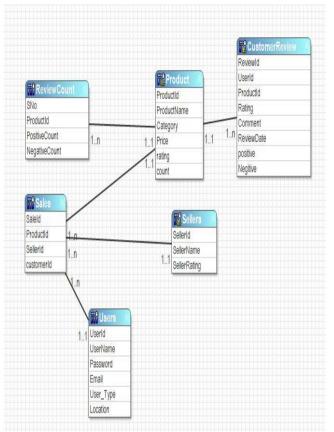
### 2. RESEARCH METHODOLOGY

The research methodology is composed of three stages. The first stage involves the Extraction, Transformation, Loading of data in Data ware house [12]. We transform the flat file into relational table as it is easy to perform the SQL operation on relation table than on a flat file.

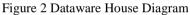
The second stage involves functions and procedures which are used to update the tables and check the type of review and rating given by the customer.

The third stage involves generating reports and creating dashboard with the help of IBM Cognos BI Software. The snapshots of three stages are given as follows.





# Figure 1 ETL STAGE



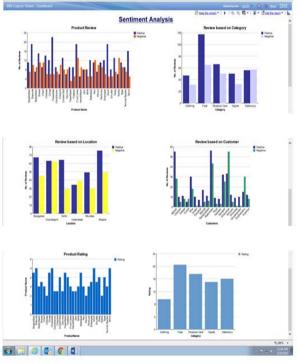


Figure 3Dashboard in IBM Cognos

# 3. STEPS IN SENTIMENT ANALYSIS (OPINION MINING)

There are basic six steps in sentimental analysis[8].

• First is information database creation,

- POS tagging is done on review,
- Features are extracted using grammar rules such as adjective + nouns so on, as noun are features and adjectives are sentiment words,
- Opinion word extraction
- Identify polarity of opinion word
- Identify polarity of sentence

There are many algorithms which can be used in sentimental analysis such as Navie Bayes Classification, Probabilistic Machine Learning approach to classify the reviews as positive or negative.

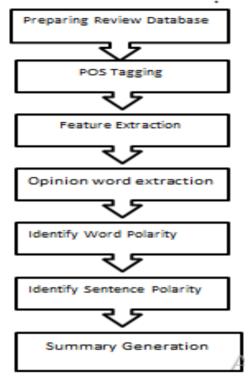


Figure 4 Basic Step of Sentimental Analysis

# 4. CLASSIFICATION OF SENTIMENTAL ANALYSIS

Sentimental Analysis of text can be mainly classified into four types which are given below.

- Document level Sentimental Analysis
- Sentence level Sentimental Analysis
- Phrase Level Sentimental Analysis
- Feature Level Sentimental Analysis
- Document level Sentimental Analysis[3]

Α.

Document level tasks primarily concerns with classification issues where the available document has to be arranged into a set of predefined classes. In subjectivity analysis a document is divided as subjective or objective. In sentiment analysis, a document can be classified as positive or negative or neutral depending upon the polarity of subjective information that is present in the document[15]. Opinion quality and support evaluation makes decision whether an opinion is useful or not and opinion spam identification groups and divides opinions as spam and not spam.

## B. Sentence level Sentimental Analysis[4]

The problem at this measure everything refers to sentences. In opinion data extraction and recovery and opinion

question answering, sentences are generally placed and positioned focused around some criteria. Opinion rundown intends to select a set of sentences which outline the opinion all the more exactly[16]. At long last, opinion mining in relative sentences incorporates recognizing similar sentences and concentrating data from them.

#### C. Phrase level Sentimental Analysis

Phrase level mining [5] came into picture because document level mining and sentence level mining approaches can not find accurately what actually users likes and they does not like. Phrase level opinion mining looks for sentiments on features of products.

#### D. Feature level Sentimental Analysis

Feature level sentimental analysis [6] comes into picture when a customer or user looking for feedback of certain feature or attribute of a product rather than total feedback of the product. We see many customers interested in only certain features of some products rather than the whole product like some people look for a mobile that has excellent battery life and they are not concerned with other features like camera clarity, music clarity and so on[7]. In situations like mentioned in this section feature level opinion mining helps a lot for extracting polarity information for a particular feature or attribute from a product.

### **5. RESULTS**

After doing ETL, creating views, modifying properties, publishing package and we plot the facts and dimensions to generate the reports to visualize the results. Firstly, to have an overview of all the reviews about the products we have a dashboard containing six different reports.

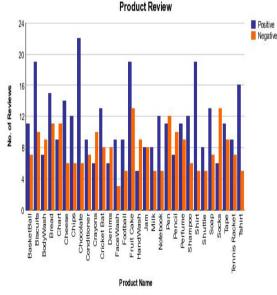


Figure 5 Positive and Negative reviews for products

- The Report above shows number of reviews given to each product. In this report number of reviews is used as measure and product name is the other dimension.
- Positive review and the negative review by the customer for each product can be seen in different color.

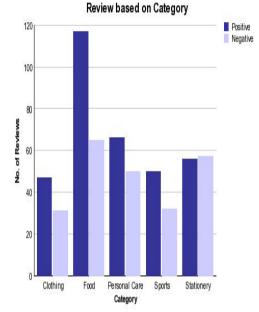


Figure 6 Reviews on the basis of Product Category

- The above report shows the positive and negative reviews of different categories of products.
- In this report number of review is fact and Product Category is the dimension.
- The report below will give number of positive and negative reviews for selected category.
- In report which is based on the location of the customer, the number of positive and negative reviews are shown on the bases of the location.
- As we can see the number of positive reviews are more in each city.

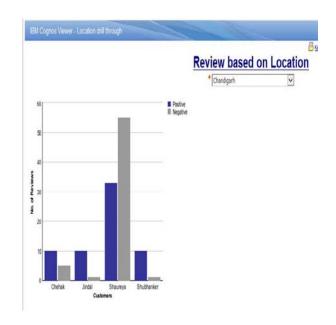


Figure 8 Reviews based on selected Location

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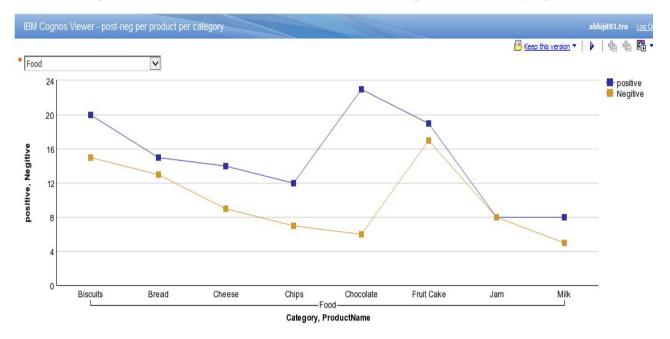
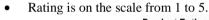


Figure7 Reviews for selected category of Product

• Rating of all Products.



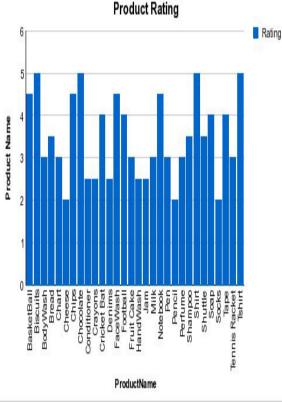


Figure 9 Rating of Products

• Category wise rating given by the customer.

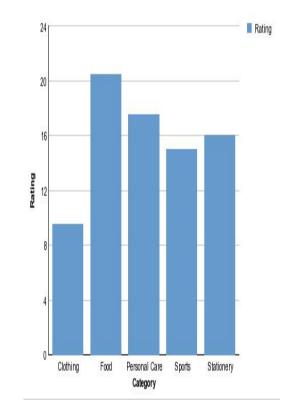


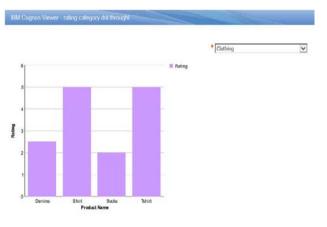
Figure 10 Rating Category

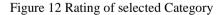
• List view of products with average of rating.



Figure 11 List View of Products with Average of Rating

- List view of products with average of rating.
- Report which we get on drill trough given below.
- These reports get filtered on the basis of particular condition.





#### 6. CONCLUSION

The following conclusions are drawn on the basis of experimental observations and analysis. SA is typically used to analyse people's sentiments opinions, appraisals, attitudes, evaluations and emotions towards such entities as organisations, products, services, individuals, topics, issues, events and their attributes, as presented online via text, video and other means of communication. These communications can fall into three broad categories, namely positive, neutral and negative.

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