



## Review Analyzer: An Opinion Mining Based System

Akshay Deepak Bhat  
Student, Computer Engineering  
K. J. Somaiya College Of Engineering  
Mumbai, Maharashtra, India  
[akshay.bhat@somaiya.edu](mailto:akshay.bhat@somaiya.edu)

Jigar Ramesh Mehta\*  
Student, Computer Engineering  
K.J.Somaiya College Of Engineering  
Mumbai, Maharashtra, India  
[jigar.mehta@somaiya.edu](mailto:jigar.mehta@somaiya.edu)

Pranav Shirish Patankar  
Student, Computer Engineering  
K.J.Somaiya College Of Engineering  
Mumbai, Maharashtra, India  
[pranav.p@somaiya.edu](mailto:pranav.p@somaiya.edu)

**Abstract:** In the last decade there has been a tremendous increase in the use of internet. People are becoming more tech savvy and are using online reviews to compare products before buying them. The field of opinion mining is hence about to boom and a huge scope for exploration exists in this field. Now a days there are various sites that offer a comparison of various products. A new problem that arises is of Opinion spam , that is, people giving fake opinions in order to try and increase or decrease the popularity of a product. This paper tries to study the various algorithms found in multiple papers.

**Keywords:** opinion mining, sentiment analysis, feature based opinion mining, density based opinion mining, aspect based opinion mining.

### I. INTRODUCTION

An important part of our information-gathering behavior has always been to find out what other people think. With the growing availability and popularity of opinion-rich resources such as online review sites and personal blogs, new opportunities and challenges arise as people now can, and do, actively use information technologies to seek out and understand the opinions of others. The sudden eruption of activity in the area of opinion mining and sentiment analysis, which deals with the computational treatment of opinion, sentiment, and subjectivity in text, has thus occurred at least in part as a direct response to the surge of interest in new systems that deal directly with opinions as a first-class object.

Some of the Applications of Opinion Mining are:

- Product ranking technologies
- Mining customer opinions on the Internet
- Sentiment Phrase Classification Vector
- Automated Course Feedback System

The two main types of opinion mining are density based opinion mining and feature based /aspect based opinion mining.

<sup>[1]</sup>DBSCAN is the algorithm used in density based opinion mining for clustering. <sup>[2]</sup>Bootstrapping is used in aspect based opinion mining during NLP.

### II. RELATED WORK

#### A. Density-based spatial clustering of applications with noise (dbscan) :

<sup>[1]</sup>DBSCAN is a data clustering algorithm. DBSCAN needs a distance function and a threshold for detecting similar objects. It uses the concept of density reachability wherein the similarity between two opinions or objects is calculated using two parameters.

The Two parameters are:-

- MinPts – Minimum number of points.
- EPS – Maximum radius of neighbourhood.

The DBSCAN algorithm starts with an arbitrary starting point which has not been visited. This point's neighbourhood is then checked, and if it contains sufficient number of points which is given by MinPts, a cluster is started. Otherwise, the point is considered noise. But this point can later be found in a large cluster. Hence, until all the points are not visited no point can be permanently termed as noise.

A point P is directly density- reachable from a point Q if there are MinPts number of points within a distance of EPS from P, and Q is one of these points .A point P is density reachable from a point Q if there is a chain of points P1,P2, . . . ,Pn , Q such that P1 is directly density-reachable from P, Pi+1 is directly density reachable from Pi and Q is directly density-reachable from Pn. Thus, a cluster can be formed starting from an arbitrary point and retrieving all points that are density-reachable from that point. If no cluster can be formed from that point then DBSCAN will visit the next point in the data set. If a cluster is formed from that point then all other points in this cluster will be used to retrieve other points which are density reachable thus

expanding the cluster. This process of finding points and forming clusters is repeated until all points are examined. The shape of the clusters formed using DBSCAN algorithm may be non-convex or elongated. The complexity of DBSCAN is  $O(N)$ .

The main advantage of DBSCAN is that it does not require one to specify the number of clusters in the data as opposed to K-Means Algorithm. DBSCAN algorithm understands the noise and separates it from the clusters. It is designed to use with databases that can accelerate region queries, e.g. Using an  $R^*$  tree. DBSCAN cannot cluster data sets well with large differences in densities, since the minPts- combination cannot then be chosen appropriately for all clusters.

**B. Bootstrapping:**

<sup>[2]</sup>Bootstrapping is a method for assigning measures of accuracy to sample estimates. This technique allows estimation of the sampling distribution of almost any statistic using only very simple methods. Generally, it falls in the broader class of resampling methods. Bootstrapping is further classified into Single Aspect Bootstrapping and Multi Aspect Bootstrapping. Multi Aspect Bootstrapping is explained below.

The working of Multi Aspect Bootstrapping can be divided into three parts.

- a. Bootstrapping Aspect related Terms for Aspect Identification.
- b. Aspect Based Sentence Segmentation.
- c. Opinion Polling Generation.

**C. Aspect Related Terms:**

<sup>[2]</sup>Aspect Related Terms (ARTs) are of two types:

- a. Nouns, verbs, adjectives and adverbs. These are similar to word-type features.
- b. Multiword terms such as bigrams or trigrams

To extract meaningful multiword terms from unlabelled reviews, <sup>[3]</sup>C-value method is used. Given a review set, a list of multiword terms is produced and ranked in the descending order of C-value score. C-value is a popular method for multiword expression extraction <sup>[3][4][5]</sup>. The linguistic filter used by C-value method is described as (noun| verb| adjective| adverb) . The C-value score of a multi-word term t can be calculated by:

- a. If t is not contained by any other terms,  
C-value(t)=  $\log(|t|) \times \text{frq}(t)$ .
- b. Otherwise,

$$\text{C-value}(t) = \log(|t|)(\text{frq}(t) - \frac{1}{n(S)} \sum_{s \in S} \text{frq}(s)), \tag{1}$$

In (1), |t| denotes the number of words contained in t, frq(t) indicates the frequency of occurrence of t in the corpus, S is the set of multiword terms containing t, and n(S) denotes the number of terms in S.

**D. Aspect Based Sentence Segmentation:**

A <sup>[2]</sup>Multi-aspect segmentation (MAS) model takes a multi-aspect sentence as input and produces multiple single-aspect segments. A segment might be a sub-sentence, or a combination of some consecutive sub-sentences. Let  $C = c1 c2 \dots$  can be a sentence consisting of n sub-sentences, and  $U = u1 u2 \dots uk$  be its segmentation consisting of k segments. The goal is to find the most likely segmentation  $U^*$  of the input sentence C by determining aspect changes

between sub-sentences. Each segment expresses a particular aspect, while contiguous segments exhibit different aspects. The formulae for Multi-Aspect Segmentation model is determined by using a <sup>[2]</sup>criterion function  $J(.)$  that evaluates each candidate segmentation U of sentence C, that is,

$$U^* \stackrel{def}{=} \arg \max_U J(C, U). \tag{2}$$

This model finds the most likely segmentation  $U^*$  with maximum  $J(.)$  score. The key is how to design an appropriate criterion function  $J(.)$  by incorporating aspect information of each sub-sentence. In the most likely segmentation  $U^*$ , two adjacent segments should express two different aspects with each segment having only one aspect.

**E. Opinion Polling Generation:**

An aspect-based opinion poll  $\phi$  can be summarized as a two-dimensional form filled with 3m (aspect, polarity) pairs and their voting scores, involving m aspects and three polarities (i.e., positive, negative, and neutral). For each (aspect, polarity) pair, its associated voting score indicates how many customer reviews have expressed it. For example,  $\Phi(\text{food}; \text{positive}) = 0:65$  indicates that 65 percent of customer reviews express positive opinions on the food aspect.

The polarity value is empirically set to +1 for a positive word and -1 for a negative word. The resulting semantic orientation value of a textual unit indicates its corresponding polarity, that is,  $> 0$  for positive,  $< 0$  for negative, and equal to 0 for neutral. In an aspect-based opinion polling task, if one aspect is not exactly expressed in the review, its corresponding polarity is considered to be neutral.

**III. CONCLUSION**

The time complexity of DBSCAN is mostly governed by the number of region Query invocations. An overall runtime complexity of DBSCAN is  $O(n \cdot \log n)$  and the algorithm needs  $O(n^2)$  memory.

**IV. ACKNOWLEDGMENT**

We would sincerely like to thank Prof. Pallavi Kulkarni(K.J.Somaiya College of Engineering) for her constant support and guidance. Her inputs during the period of research were highly valuable and helpful.

**V. REFERENCES**

- [1]. Christopher C. Yang and Tobun Dorbin Ng, Member, IEEE :“Analyzing and Visualizing Web Opinion Development and Social Interactions With Density-Based Clustering”, 1083-4427/\$26.00 © 2011 IEEE
- [2]. Jingbo Zhu, Member, IEEE, Huizhen Wang, Muhua Zhu, Benjamin K. Tsou, Member, IEEE, and Matthew Ma, Senior Member,IEEE:“Aspect-Based Opinion Polling from Customer Reviews”, 1949-3045/11/\$26.00 \_ 2011 IEEE
- [3]. K. Frantzi, S. Ananiadou, and H. Mima, “Automatic Recognition of Multi-Word Terms: The C-Value/NC-Value Method,” Int’l J.Digital Libraries, vol. 3, pp. 115-130, 2000.
- [4]. E. Milios, Y. Zhang, B. He, and L. Dong, “Automatic Term Extraction and Document Similarity in Special Text

- Corpora,” Proc. Sixth Conf. Pacific Assoc. for Computational Linguistics, pp. 275- 284, 2003.
- [5]. M. Krauthammer and G. Nenadic, “Term Identification in the Biomedical Literature,” J. Biomedical Informatics, vol. 37, no. 6, pp. 512-526, 2004.