Sentiment Analysis of Opinions in Amazon Customer Reviews

[1]Vidhan Raut, [2]Zaheer Shaikh, [3]Shrikrishna Kadam, [4]Piyush Sarode, [5]Vishal Kumar, [6]Sumit Rana

[123456]Department of IT & [123456]Department of MCA.
[123456]Vishwakarma Institute of Technology, Pune, India.

***Abstract*: online retailers routinely ask for feedback of the products and related services from their customers. Whilst e-commerce gets increasingly popular, the strength of customer evaluations for a product swiftly increases. A popular product may have several hundred reviews. As a result, it can be hard for a prospective consumer to read them and make a buying decision. The goal of this project is to aggregate every customer review of a certain product. This summary work is differ from typical text summarization in that we are only focused on certain qualities that consumers are enthusiastic about—and whether those opinions are either favourable or negative. We do not paraphrase the reviews by choosing or rephrasing a part of original statements from the reviews to emphasise their important points, as text summarization done in a traditional way. In this article, we solely mine opinions and product attributes that have received comments from reviewers. Numerous methods are offered to mine such features. Results from our trial indicate how highly successful these methods are.**

Keywords: Sentiment Analysis, Product review, Amazon Reviews, consumers review, Review analysis.

I. INTRODUCTION:

As the acceptance of and use of the internet for e-commerce activities increases, more products are offered for sale online. At certain major retailer websites, certain well-liked products can receive hundreds of reviews. As a result, it is extraordinarily difficult for an average buyer to read such reviews and decide whether or not to purchase the items. In this work, we propose a brief summary of feedback from customers based on the features of a digitally-sold product. The task will require two steps to be completed:

1. Determine the product qualities about which people have conveyed their opinions (referred to as opinion features) and rate them depending on the frequency with which they occur in the reviews.

2. We count the number of positive and negative customer reviews for each feature. Specific reviews expressing these opinions are linked with the feature. This makes going through the reviews simpler for future consumers.[8]

We will simply focus on the first phases of obtaining and gathering reviews from websites. Specifically, we will mine just the characteristics of the items on which consumers have remarked, and after that we'll assess if an opinion is either favorable or negative [11].

II. RELATED WORK:

We will consider two main areas: terminology identification and text summarization. A major portion of text summarization techniques fall in either text extraction or template instantiation. This project's work is distinct in that we do not take out the text that most precisely portrays the phrase, but rather locate and take out those keywords and analyse the views connected with them. Kan and McKeown suggest a fusion of methods that combines instantiation of a template and extraction of sentence.[13] Boguraev & Kennedy also describe a strategy for identifying some of the key phrases, objects, and incidents in a document & using them for assisting in summarizing the material. Proposed approach is unique in that we must discover all keywords in a list of customer reviews, irrespective of how significant they are. [8]

III. LITERATURE REVIEW:

A. *Identifying the Pros and Cons of given user Reviews:*

We offer an automatic system that will analyse the given user evaluations and separate the positives and negatives. Our goal is to identify the justifications for the opinions, which could be either facts or opinions in and of themselves. According to the findings of our experiments, the final system can identify professionals with 66% precision and 76% recall.[1]

B. *Thumbs up - Machine Learning Methods for Sentiment Classification:*

This research considered the problem of categorising documents by the overall sentiment. Out of the machine learning methods described by the authors the Support Vector Machine (SVM) methods tend to outperform the Naives Bayes method. We conclude that even though a human could easily detect the true sentiment of the review, the detection of sentiment by a machine will require application of more advanced techniques.[2]

C. *Intensity of Sentiment Using Sentiment carrying word Embeddings to sort Adjectives:*

In this study, the author offers0 a semi-supervised method for ranking adjectives with similar semantic properties by employing sentiment-bearing word embeddings. With respect to the gold standard ranking, our method exhibits a significant Spearman's rank correlation of 0.83. We demonstrate how sentiment-bearing word embeddings enable a method for more precise intensity ranking.[3]

D. Sentiment analysis of online consumer reviews with DLMNN and web - based product prediction with IANFIS:

The author proposes the Deep learning modified neural network (DLMNN) methodology for sentiment analysis or product review available online and an Improved adaptive neuro-fuzzy inference system (IANFIS) methodology for predicting and suggesting various products [4] After comparing the performance of the two different methodologies the author suggests that IANFIS and CLB scenario from DLMNN overall work best for future prediction and sentiment analysis of the products review.[4]

E. Using contexts from extraction pattern learning, a bootstrapping method for learning a semantic sentiment lexicon:

This paper describes the Basilisk bootstrapping algorithm, which creates improved semantic lexicon for a variety of categories. Basilisk starts with an unlabelled dataset and provides terms for each semantic variety in order to discover new words. Basilisk generates a semantic class hypothesis for every word based on an extensive amount of extraction pattern contexts and cumulative data. On the basis of six semantic categories, Basilisk is rated. Compared to previous methods, Basilisk's semantic lexicons are more precise, with several categories exhibiting notable advancements.[7]

F. Sentiment Analysis and Subjectivity:

Facts and opinions are the two primary categories into which information in text format in the world can really be broadly classified. Facts are expressions of beings, events, and their attributes that are objective in nature. Opinions are irrational utterances that convey people's opinions, assessments, or attitudes concerning things, events, and things in general. The mining and retrieval of factual information has been a major focus of recent research on textual information processing.[8]

IV. THE PROPOSED SYSTEM:

Fig.1 depicts the suggested summarising system's architectural layout. The summarising process is divided into two major steps: identifying opinion direction and extracting characteristics. The product reviews serve as inputs to the system. The summary of reviews is supplied as output, as mentioned in the introduction.[7]

The program will first download all of the customer feedback and save them in a review database, based on the data entered. The subject of this work is the "extraction function," which discovers that far too many reviewers have voiced thoughts in their evaluations and then finds the unique insights. The function "opinion orientation identification" retrieves the created attributes and categorises them as either favourable or negative. Natural language processing part-of-speech tagging is known as POS [5]. The next sections go through each feature extraction technique in turn. Because the purpose of our method is to identify whether people like or detest a suggested product, we will not describe the final stage, "keyword application," because it is not the topic of
Our work and is difficult.

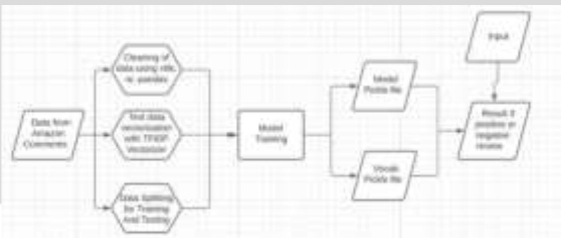

Fig. 1 The opinion keyword extraction system

As a result, determining which characteristics of a product are most discussed is a critical stage. However, due to the complexities of interpreting real language, some phrase forms are difficult to deal with [7]. Check out the following simple and sophisticated statements from digital camera feedback:

"The pictures are very good."

"Overall a fantastic, very compact camera."

The first phrase explains the cameras look as seen by the user in terms of image quality. In a similar spirit, the second statement reveals that the user is expressing an opinion regarding the camera as a functionality [10]. While some of the features in these sentences are clear, others are hidden and harder to identify. As an example

"While light, it will not easily fit in pockets."

This consumer is referring to the camera's size, however the term "size" is not used explicitly in the review [9]. Understanding the content and context of human language and delivering it to artificial intelligence using sophisticated approaches is necessary to recognise such qualities. However, implicit traits are significantly less prevalent than explicit ones. As a result, in this study, we concentrate on detecting characteristics that appear specifically as nouns or noun phrases [8]. Each sentence and word will be stored in the review database. A transaction file is prepared in the following phase in preparation for the creation of common features. Each line in this document comprises sentence-related terms, the overwhelming majority of them being pre-processed nouns/noun phrases. This is done to ensure that additional sentence components do not become product attributes. Stopword elimination, stemming, and fuzzy matching are all examples of pre-processing in this context. In order to cope with word variants or misspelt terms, fuzzy matching is used. Consider this: the names "autofocus" and "auto-focus" keep quoting the same feature.[8] "Autofocus" is always replaced with "auto-focus."

V. FREQUENT KEYWORD GENERATION:

This stage involves locating the most often used terms. We use association rule mining to determine every keyword itemsets in order to perform this task. A set of phrases or words that come together and in our context is referred to as an itemset.

An explanation of association rule mining is provided below: Let I = i1,..., be an object collection, and D be a transaction collection (the dataset). Every transaction holds a subset of the items in I[8] . An implication of the type XY is a rule of association, where X I, Y I, and X Y =. If c% of transactions in D that support X also support Y, then the rule X Y holds with confidence c in D[9] The rule has s in D support, if s% of transactions in D contain X Y. The problems of association rules are that the outcomes should be more engaging, have more support, and be more understandable.

Mining frequently occurring phrases: The above-mentioned data is kept in a dataset referred to as a transaction set. CBA, an association rule mining based on the Apriori technique, is then used (Agrawal and Srikant 1994)[11]. It locates all frequently occurring sets of data in the transaction set. Each frequently occurring tuple that emerges is a possible feature. In this work, If a tuple appears in at least 1% (minimum assistance) of the review terms, it is deemed frequent. It discovers all sequential patterns from a collection of transactions that fulfil a user-specified minimum support in the first phase. It generates rules [11] in its second step using the discovered frequent item sets. We just require the first part of our job, which is to identify frequently occurring itemsets that are suitable keywords. Furthermore, because we assume that a product keyword has no more than three words, we just need to locate frequent item sets with three words or less in this task (this restriction can be easily relaxed).[11] The resulting data items, also known as candidate keywords, are added to the keyword set for subsequent processing in this task.

VI. Keyword Pruning:

All of the frequently occurring keywords discovered through association mining are either irrelevant or false. There are some keywords that are also tedious and repetitive. The goal of keyword pruning is to remove these undesirable keywords. Pruning can be further divided into two types and they are as follows:

Compactness pruning: Using this technique, we examine features that have keyword phrases of at least two words and filter out meaningless ones… [14]

In an association mining transaction, the item's location is ignored. Words that are grouped together and in a certain sequence in a natural language sentence, on the other hand, are more likely to be helpful phrases. As a result, certain created and frequently occurring feature phrases may turn out to be fake features. The purpose of compactness trimming is to completely remove candidate keywords that comprise words that do not occur together within the same sentence. To prune, we utilise the distances between words in a candidate keyword phrase (itemset).

Definition 1 - *compact phrase*

- Let us designate f as a commonly used feature phrase with n words. Say a sentence s includes f, and the order of the terms in f that appear in s is: w1, w2,..., wn. If a word falls between any two words next to it, (wi and wi+1) in the subsequent pattern is less than three, f is compact in s.[14]

- If f exists in m sentences in the review database and is judged to be compact in at least two of the m sentences, we refer to f as a compact keyword phrase.[14]

For instance, we have commonly utilised feature phrases such as "digital camera," which is included by three words from the review dataset:

"I had searched for a digital camera for 3 months."

"This is the best digital camera on the market"

"The camera does not have a digital zoom"

The term "digital camera is compact" appears in both the first and the second phrase but not in the third. It is, nonetheless, a compact sentence because it did occur compactly twice [14].

We examine whether a feature phrase and the sentence in which it appears are consolidated in the sentence. If we can't find two brief statements in the review dataset, we cut the keyword phrase.

VII. Redundancy pruning:

This step focuses on removing redundant features that contain only one word. Redundant features is defined as:

Definition 2 *p-support (pure support)* feature: P-support feature is the percentage of sentences in which the feature appears as a noun or noun phrase without another feature phrase that is a superset of the feature. In association mining, P-support varies from general support [14]. As an example, our feature manual includes ten words to back it up. It is a subset of the review database feature phrases manual mode and manual setup. Suppose there is support for two keyword phrases (4 and 3), no sentence combines these two phrases concurrently, and all terms are as noun or the noun phrases, then the p-support of manuals is 3. Keeping in mind that we may not want adjectives or adverbs as keywords, we want the key phrase to be a noun or a noun phrase. We utilised the basic p-support to eliminate such repeating phrases.A key phrase is eliminated if it is a derivative of another keyword or phrase and has a p-support lower than the minimal p-support, which in our system is set to 3 (indicating that the keyword alone might not be significant). For example, while life is not a particularly useful feature in and of itself, battery capacity is a meaningful feature word [14]. It does not eliminate the previous manual example that has a p-support of 3. This makes sense given that the term "manual" has two interpretations: noun ("references") and adjective ("guidelines") ("of or connected to hands"). As a consequence, all three manual operations, mode, and configuration, may be enticing.

VIII. Opinion Words Extraction:

People tend to use opinion words to communicate their good and critical sentiments. After seeing that individuals commonly convey their thoughts about uniqueness of a product using opinion words which are positioned around the feature in the sentence, Using all of the other common traits, we can recover opinion words from the review dataset.

Consider the following two statements as examples:

“The strap is horrible and gets in the way of parts of the camera you need access to.” “After nearly 800 pictures I have found that this camera takes incredible pictures.”

In the first paragraph, the strap characteristic is close to the viewpoint of the term awful. In the latter example, the opinion word astounding is more closely associated with the feature photos. [14] If a phrase in the review database includes a common trait, we get the neighbouring adjective based on our discoveries. When an adjective of this type is identified, it is designated as a term of opinion. A close adjective is one that modifies a correlation - based feature noun or noun phrase.

As observed in the prior example, the adjective that actually changes the strap is of low quality, but the attribute that modifies the image is of exceptional quality. We handle word variations and typographical errors via derivation and imprecise matching [14]. Using this approach, we generate an opinion set of words for further usage.

IX. Opinion Sentence Orientation Identification:

Following the identification of opinion characteristics, we determine the semantic orientation (favourable or unfavourable) of each opinion statement. This is divided into two steps: (1) We determine the semantic orientation of each opinion word in the opinion word list using a bootstrapping approach using WordNet, and (2) we decide the opinion orientation of each phrase based on the prevailing leanings of the opinion words in the sentence [14]. The details may be published in a subsequent study.

X. Infrequent Keyword Identification:

The "hot" features for a given product that users are most interested in are the frequent features. However, there may be some specific features that interest only a minute number of probable consumers. Extracting the above mentioned infrequent features is the main question here

Consider the sentences below:

“Red eye is very easy to correct.”

“The camera has an excellent easy to install Software”

“The pictures are absolutely amazing” “The software that comes with it is amazing”

The first along with second sentences describe different features, but they both express the same opinion keyword: the first line is about the red eye, while the second line refers to software. Assume that the frequent feature in the earlier review databases of digital cameras is a frequent feature. Red eyes are infrequent but also interesting. Likewise, the word remarkable occurs in both the third and fourth phrases, but the third statement is about photos while the fourth statement is about software. Analysing the above example, we notice that people may use same or similar adjectives to describe different subject matter. As a result, features that were not discovered during the step of frequent feature generation can use opinion words. We try to locate the neighbouring opinion word by using frequent features that change the features in the opinion word generation step.In accordance with the step, we utilise the specified opinion words so that to maintain a close feature that the opinion words alter. In one and the other steps, we utilise the scrutiny "opinions tend to appear closely together with features". Using the procedure mentioned below we try to extract infrequent features:

- Find the imminent noun or the noun phrase of the opinion word for each of the sentences in the database we are reviewing if it contains only opinion words and does not contain any frequent feature. The noun or the noun phrase is then saved as an infrequent feature in the feature set. Because this is the most common case, as the noun or the noun phrase that perhaps perspective term changes, we use the imminent noun or the noun phrase. Instead, we use this uncomplicated interrogative approach to identify the nearest noun or the noun phrase because trying to find the respective noun or noun phrase that an opinion word alters necessitates acknowledging of the naturally spoken language, which is gruelling with only POS tags. It's quite effective [14]. One of the problems with using opinion words for infrequently feature identification is that irrelevant nouns/phrases of the given product are also found by the system. Since people use common words to describe the products, including both the important features as well as irrelevant descriptions. Taking the following into consideration,

"The salesman was easygoing and let me try all the models on display."

A salesperson isn't the main element of the product, yet it'll be identified as a unique feature due to the subsequent opinion term simple [14]. This is not a major concern because the count of rare characteristics is small in comparison to the amount of frequent aspects. According to our experimental observations, they contribute for around 15- 20% of the whole countings of features. For completeness, infrequent features are spawned. Furthermore, frequent features are extra relevant than infrequent ones.Because we prioritise features based on their p-supports, features that occur frequently will be generally recognized as low priority, affecting the majority of users.[14]

XI. RESULT AND DISCUSSION:

There are 4 components to this project-Review analysis for Etsy, Word Count, Dropdown Review analysis and analyse review. The "review analysis for etsy" section shows the result of the reviews scraped from etsy in the form of a pie chart. The pie chart shows the number of positive and negative reviews and their percentages. The "Word Cloud" section of the project displays the image with the word cloud of the reviews. This image shows keywords which have the most frequency that have appeared in the reviews. The keywords in bigger font have the most frequency then the word appeared in small words. The "Dropdown review analysis" has a drop down menu which has the top reviews, which could be selected to see the result- positive or negative. The "analysis review" section has a text field which provides the real-time response of the review, as positive or negative.

Fig. 2 Amazon Review Sentiment Analysis

Fig. 3 Illustration of positive review

Fig. 4 Illustration of negative review

This project has a real-time analysis which could give the result instantaneously without any need to run the program again and again. This feature is useful in cases where quick results are required. Furthermore, this project has the feature of word cloud which will show the most occurrence of keywords in an attractive manner. The user could easily distinguish the most occurring keywords. This project has a dropdown menu which makes it easy to see the result of the review. The user can select the review in the dropdown menu to see its result.

XII.CONCLUSION:

Depending upon the various data mining & natural language processing methodologies, we provided and also suggested numerous ways for mining opinion aspects from product reviews in the study. The goal is to create a keyword map from a huge number of customer evaluations of an online-sold product. We feel that as more individuals buy and voice their ideas on the Internet, this problem will become more serious. Our project findings show that the recommended strategies are effective at their jobs. We may refactor the following approaches in the future. We also want to categorise features based on the strength of the comments given about them, for example, to determine which aspects consumers highly favour and detest. This will boost feature extraction and successive summarization even more.

ACKNOWLEDGEMENT:

We would like to express our deep gratitude to Professor Pankaj Kunekar, for his patient guidance, enthusiastic encouragement and useful critiques of this work and for his advice and assistance in keeping the progress on schedule.

We would also like to extend our thanks to each team member for their hard work and for giving their time so generously.

Finally, we wish to thank our parents for their support and encouragement throughout our studies.

REFERENCES:

1. Soo-Min Kim and Eduard Hovy "*Automatic Identification of Pro and Con Reasons in Online Reviews*" USC Information Sciences Institute
2. Shivakumar Vaithyanathan, Bo Pang and Lillian Lee "*Thumbs up? Sentiment Classification using Machine Learning Techniques*" Cornell University and IBM Almaden Research Center
3. Raksha Sharma, Arpan Somani, Lakshya Kumar, Pushpak Bhattacharyya "*Sentiment Intensity Ranking among Adjectives Using Sentiment Bearing Word Embeddings*" Dept. of Computer Science and Engineering IIT Bombay, India
4. P. Sasikala and L. Mary Immaculate Sheela "*Sentiment analysis of online product reviews using DLMNN and future prediction of online product using IANFIS*" Mother Teresa Women's University, Kodaikanal, India (2020)
5. Andranik Tumasjan, Timm O. Sprenger, Philipp G. Sandner, Isabell M. Welpe "*Predicting Elections with Twitter: What 140 Characters Reveal about Political Sentiment* " Technical University of Munich
6. Ioannis Korkontzelos,a, Azadeh Nikfarjam,b Matthew Shardlow,a Abeed Sarker,b Sophia Ananiadou,a,1 and Graciela H. Gonzalez "*Analysis of the effect of sentiment analysis on extracting adverse drug reactions from tweets and forum posts*" National Centre for Text Mining, School of Computer Science, University of Manchester, Manchester Institute of Biotechnology
7. [7] Michael Thelen and Ellen Riloff "*A bootstrapping method for learning semantic lexicons using extraction pattern contexts*" University of Utah, Salt Lake City, UT (2002)
8. Bing Liu "*Sentiment Analysis and Subjectivity*" Department of Computer Science, University of Illinois at Chicago (2010)
9. Bing Liu "*Sentiment Analysis and Opinion Mining*" Morgan & Claypool Publishers, May (2012)
10. Andrew Ortony, Gerald L. Clore and Allan Collins "*The Cognitive Structure of Emotions*" University of Illinois at Urbana-Champaign
11. Agrawal, R. and Srikant, R. 1994. "*Fast algorithm for mining association rules.*" VLDB'94, 1994.
12. Barzilay, R., and Elhadad, M. 1997. *Using lexical chains for text summarization. ACL Workshop on Intelligent, scalable text summarization*.
13. Boguraev, B., and Kennedy, C. 1997. *Salience-based content characterization of text documents. In Proceedings of the ACL*
14. Minqing Hu and Bing Liu "*Mining Opinion Features in Customer Reviews*" Department of Computer Science University of Illinois at Chicago