

Final Aggregated Score and Concise Opinion Output Generation For Product Reviews From E-commerce Platforms

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Abstract

Peoples opinions and experiences are some of the most pivotal information that people tend to use in decision making process. Today, almost every E-commerce vendor provides a platform for users to provide feedback on the various products and services they avail from the internet and they are present in thousands, for even a single product. It is, therefore, not feasible to go through all of them. In this paper, we aim at proposing a methodology to accumulate all the necessary information from the reviews and present the users with a short, crisp and summarized version of the reviews along with other key informations that a review page may provide. Hence we aim at reducing the user's overhead in going through all the reviews to make a decision. Instead, the system does that work for the user. By using machine learning techniques like sentiment analysis, opinion summarization, product aspect extraction, etc we extract all the necessary information to produce the final

output - Final Aggregate Score (FAS) and Concise Opinion Output (COO). Reviews extracted from E-commerce sites or from Yelp and Amazon's review database are used for testing. This is a two-fold model, first of which is scoring the products/service based on the ratings of reviews, overall rating of the product, sentiment analysis score from all the reviews, user credibility score and combining them all to present a rating (out of 10) for the product. The second module aims at providing a summarized output after analysing all the reviews by using text summarization techniques along with a list of pros and cons. Hence, the two modules combined, will greatly reduce the tiresome job to go through all the reviews to come to a decision.

Keywords : Sentiment Analysis, Opinion Summarization, Opinion Mining, Feature Extraction, Review Based Opinion Mining.

1 Introduction

E-commerce has given user's a chance to share their views about a product they have purchased or used and users too have taken it as benefiting and are expressing openly. Users have varied views and opinions about a product and over that there are different ways to express those opinions which makes it a huge chunk of opinions that may be similar yet varying in words. Thus, it is a much necessary task to clean these opinion records and to publish a minimized, concise output while combining all the reviews. Sentiment analysis or opinion mining are the domain which deals with the extraction of exact sentiments of a reviewers from their review to produce a brief straight forward review. Sentiment analysis is the process of extracting emotions or opinions from a phrase/para/text for a given product/topic[1]. It allow us to understand the attitudes, opinions and emotions in the text. It involves predicting or analyzing the hidden information present in the text. Also, there are various important notions to be discussed under the topic of Sentiment Analysis, such as Subjectivity/Objectivity, Polarity, Level of Sentiment and these can be defined as the righteous steps to meet the end-point of getting a perfect output over finding the exact sentiment

of the user. The reviews can be classified as subjective or objective based on its content such as the one with a sentiment would be subjective while the one which is a fact would be classified as objective. For eg.: Objective: I went to the Nike Store. Subjective: To purchase the Nike 2000X which are the best in running shoes. This example clears the idea of subjectivity and objectivity. The Polarity of the review gives a classification on the sentiment to be specific as to positive negative or neutral. The level of Sentiment can be recognised as the value of how deep an assessment was made say document level, sentence level or phrase level but for the purpose of review classification we need the second (Sentence Level). Sentiment classification is a technique of text classification with the objective to classify a text according to the sentimental polarities of opinions it contains e.g., favorable or unfavorable, positive or negative[1]. Various techniques have been introduced to extract the exact level of sentiments from the word blocks. Some of which are sentiment classification using Support Vector Machine, Naive Bayes and Maximum Entropy. It is well known that as the days pass by, the data on the Internet increasing exponentially and so the data related to products such as reviews. Thus, it has become a necessity to provide a summary to them so that the user does not have to go through the complex task of processing all the facts, opinions and ratings and has to read all the reviews as given by the other people and also to interpret and to compare them. Thus, here opinion summarization comes into picture. Opinion Summarization is the process of analysing the text and to produce a concise laconic output which is brief and depicts the exact meaning of the complete text analysed. This could result in much shorter or maybe upto a word summary of all the text analysed by it so as to provide the gist of the overall text or reviews providing the users with a brief easy to process without complexity valued word that can be trusted and believed upon. The main data sources for the reviews are websites such as YELP or micro-blogging or Social Networking or e-commerce sites for example Amazon, Flipkart etc. This paper proposes two modules on which the complete system is based, namely, Final Aggregate Score (FAS) and Concise Opinion Output (COO). FAS being the first step which includes scoring on the basis of the various elements of a review like reviewers rating for the product, upvotes or downvotes on each review, sentiment analysis

score of the review text, reviewer credibility score the overall rating of the product. All the aspects are converted to scores and used to give an overall score to the reviews. COO is the second step which uses product aspect extraction and text summarization to crunch all the review text and thereby produce a short crisp version of the reviews along with a list of pros and cons, helping the user to make the decision in one go. Figure 1 shows the current scenario and figure 2 depicts our system design.

2 EXPERIMENTAL PROCEDURE

The schematic representation of the test setup is appeared in this warmth exchange test set up demonstrated is worked as a shut circle framework comprising of a store tank (14 liters), a pump, a detour line, a warmth exchange test area, a water cooler and a stream meter. The warmth exchange segment has a rectangular cross-segment zone (200 cm²) with length and broadness of 20mm and 10mm separately and was produced utilizing copper paper (1 mm thickness); and the aggregate length were 700mm.



Figure 1 A lot of reviews to be read before finalizing the purchase(Current Review System).



Figure 2 Overall System Implementation

3 LITERATURE REVIEW

This whole process can be broadly divided into three major sections i.e. extraction, analysis and score calculations. There have been a great deal of research on how each of these can be accomplished though not efficient yet productive to the overall domain. Extraction of reviews was performed using various Web Development tools such as JQuery, JSON, JS and a few others to extract out the data of reviews[11]. However, the results werent formulated into any proper format. Using JSON objects to classify and collect the data into a proper manner so that it could be useful.and reduces the extra load of filtering and sorting of the data. Analysis of the sentiment of the text from the review. How and what exactly the reviewer wishes to say about the product. Huge researches have been done and various ways methods have been demonstrated regarding it such as Sentiment Polarity, Subjectivity Detection, Term presence vs Frequency Single Document Opinion Oriented summarization[1, 2]. All this can provide a proper and extensive as well as deep thought on the review. Also, there is an AFINN list [12] which provides a list of words and their existing polarity level which could be between -5 to +5 and has proven to be 77% accurate. Using AFINN list alongside two APIs mention thereafter to produce a more favourable and accurate result. Score Calculation and weightage has been an important part of this TOPIC research scope and have developed our own algorithm to calculate each of these and have mention in detail in sections III.

4 FAS SYSTEM DESIGN IMPLEMENTATION

4.1 Detailed Review Extraction

Since there are a lot of E-Commerce sites and some give access directly to their review system through APIs while some sites don't have such APIs. Taking a new direction to access all these reviews. It will be specific for each E-commerce site and thus would be highly appropriate for each site. The process would be to use JavaScript to get the tags based on the website already opened in the web browser and then accessing and extracting the particular details, all to be done to store in JSON format so that it could be easily manipulated later and made accessible for the second phase

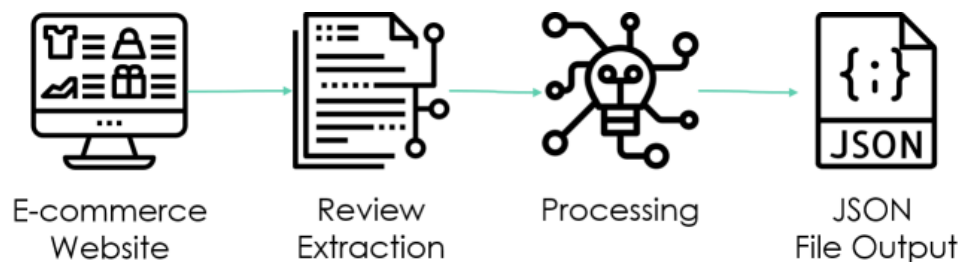


Figure 3 Review Extraction Process

i.e. Sentimental analysis. Also details related to the product be extracted so that machine can learn which all consumers are applicable to review for which all types of products. Fig 3 depicts the actual process.

4.2 Product Aspect Extraction

Chien-Liang Liu et al. [3] makes use of Latent-Semantic-Analysis-Based-Product Feature identification. LSA is a Natural Language Processing technique. It analyses relationships between a set of documents and the terms that they contain by exploiting the related concepts between those terms. A word matrix constructed from the document and the technique SVD (Single Value Decomposition) is used to reduce and normalise the matrix. The matrix cells are then

compared by taking cosine vector product. Similar words are near to 1, while dissimilar closer to 0.

4.3 Reviewer Credibility Check

Given that E-commerce websites are one the most exponentially growing platforms with almost a billion users everyday. It might also be the major source of unhelpful and fake reviews. Also for a proper recommendation that the algorithm seeks to provide to our users, it is important that the credibility of the reviewer is checked. The credibility check is based on various factors and details of the reviewer. The output of this check is also score based. Hence for example, a professional photographer who is recommending a camera on the new Motorola phone will get the highest score out of the group of, say, four people, including an Android Developer (who scores second), a college student studying in IT field (scoring third) and a housewife (scoring last). Almost all available details of the user will be used to bring out as much correlation possible between the reviewer and the product in question. Fig 4 shows this process in an illustration.

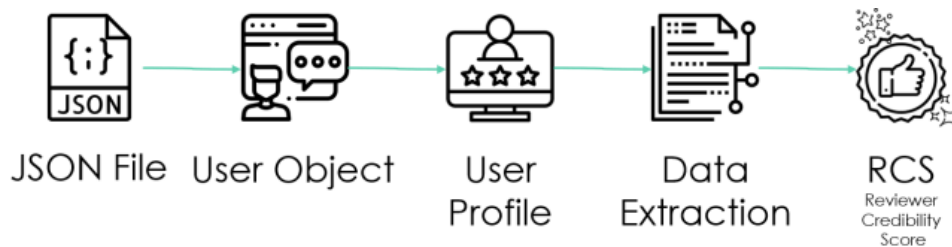


Figure 4 Reviewer Credibility Check

Example: Product: Phone

Scores are provided to a reviewer based on how closely he is related to the category of product he is reviewing about, or is professionally in the same field, is certified or endorsed and the number of reviews he has previously posted.

Table 1: Example for reviewers to category relation

Reviewer	Score
Android Developer	+10
IT student	+8
Housewife	+2

Table 2: Product Category to Reviewers aspects comparison and scoring

Reviewers Aspect	Max Score
Occupation	+12
Education	+12
Certified In	+15
Interests	+10
Endorsements	+7
Reviewed Item	+3/per review

4.4 Sentiment Analysis of Review

Sentimental Analysis is already a widely used technique to systematically identify, extract and quantify subjective information, widely applied to reviews and survey responses to derive the attitude of the speaker. It is mainly based on lexical polarities, ie, separating and grouping individual words into positive, negative and neutral groups and assigning values on the basis of their impact in the sentence and context they are used. Using Lexalytics and thesay.io API to get a well described analysis of the reviews along with a confidence score to be used to produce the FAS score and the concise opinion output to recommend. Also, simultaneously using the Node JS packages such as Sentiment, wink-sentiment, ml-sentiment and other libraries so as to get a precise score based on all these packages. The one important aspect of these packages is the AFINN list 2.0 that contains around 2417 words that contains scores from -5 to +5 for each word and when tested produced a exact score of 77% accuracy. Also, when it is implemented with others libraries can produce and score upto 3% higher that makes it 80% to be accurate. This qualifies the highest level of insurance

of the review validity as upvotes are also used that is if the review was useful for other buyers and if its high the review that directly implies that the review is genuine and worthy of trust. Hence, increasing the overall review quality to or over 81% accuracy.

4.5 Final Aggregated Score Formulation

This is one of the most important feature of our proposed system. To provide our users with a Final Score that takes into account

1. Individual ratings from reviews
2. Reviewer Credibility Score
3. Review score from sentimental analysis of the reviews
4. Upvote/Downvote counts on individual reviews
5. Overall rating of the product on site.

Table 3: Weightage Distribution

Aspect	Weightage
Reviewer’s credibility score	30
Sentiment Analysis	30
User Rated	30
Upvotes/Downvotes	10

These various factors are part of the FAS algorithm that provide users with a single Rating scoring out of 100, which will make it easier for them to make decisions. Following are the factors to calculate FAS Reviewers Credibility[RC] User rated [UR] Sentiment Score[S] Upvotes/Downvotes[UD] Overall Rating [OR]

Then review score[RS] is calculated as - $RS = (RC + (S \cdot 0.30) + (UD \cdot 10) + (UR \cdot 20)) \dots(i)$ Then FAS is calculated as- (with Review score weightage as 50

$$FAS = (RS/No. \text{ of Reviews}) + (OR)]/10 \dots(ii)$$

The FAS score is then rounded off to nearest multiple of 5 and the score then COO matches with the corresponding output.

4.6 Concise Opinion Output

The Concise Opinion Output part makes the second most important factor of our system. Using Product aspect extraction and text summarization the system aims at presenting the user with a short and crisp but equally informative output that carries almost all the information required to make the decision to or not to buy the product. It aims to provide a recommendation statement produced from the analysis of the various reviews on the product. It will also contain a list of pros and cons of the product, along with the FAS (score) to highlight the overall rating of the product as computed by our system. The recommendation note would be based on the FAS score which ranges from 0-10 hence a note of recommendation derived and produced to the new buyer so as to make their research easier and direct.

Table 4: COO corresponding to the FAS.

FAS	COO
0	Not Recommended
1	Very Poor
2	Poor
3	Do-able
4	Average
5	Good
6	Very Good
7	Recommended
8	Excellent
9	Go for It

5 DISCUSSION

Although people largely rely on the overall ratings of the product, there are many other factors that are not often taken into consideration. Our system aims at analysing the reviews at a deeper level while at the same time greatly reducing the overhead of the user to go through everything to come to a decision. Example: Consider

the following scores to be for each of the aspects for 3 reviews with Overall Rating of 4.5

Factor Review 1 Review 2 Review 3 RC 76 90 45 UR 3.5 4 5 S 37 24 40 UD 16 24 0 RS 56.5 60.6 55.5

Table 5: Review Score calculation (using eq. 1)

Factor Review3	Review1	Review2
RC	76	90
45		
UR	3.5	4
5		
S	37	24
40		
UD	16	24
0		
RS	56.5	
60.6	55.5	

$$RS/\text{No.of Reviews} = 57.5$$

Therefore FAS = 73.75, (using eq. 2) Hence the COO would recommend it as Recommended.

It is clear the algorithm takes into account all the necessary aspects attached to the set of reviews and formulates a suggestion/recommendation that considers not only the review text but also who wrote the review, how others found it useful and his perspective towards the product/service. Though the overall rating of the product was 4.5/5 or 9/10, the algorithm computed the FAS score of 7/10 which compared to the overall rating is lesser because it tries to capture all possible factors in hand and still recommends the product satisfactorily.

6 CONCLUSION

As discussed above, it is a recommendation system that eases up the overload on the user to go through multiple reviews, automating the users task, it sifts through all the reviews and related aspects,

computes scores for the various factors and utilizes that score to recommend a product/service. Although the computed scores are often lesser than the overall rating, they do capture and compute more information than a simple averaged rating. Thus it is safe to say that the algorithm has eventually increased the quality of the reviews as a result.

References

- [1] . Pang B, Lee L., Opinion mining and sentiment analysis Found Trends Inform Retrieval: 1135, 2008.
- [2] . Bo Pang, Lillian Lee and Shivakumar Vaithyanathan Thumbs up? Sentiment Classification using Machine Learning Techniques 2008.
- [3] . Harpreet Kaur, Veenu Mangat, Nidhi, A Survey of Sentiment Analysis techniques , International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC 2017) 2017.
- [4] . Jayashri Khairnar , Mayura Kinikar, Machine Learning Algorithms for Opinion Mining and Sentiment Classification, International Journal of Scientific and Research Publications, Volume 3, Issue 6, June 2013.
- [5] . Chien-Liang Liu, Wen-Hoar Hsaio, Chia-Hoang Lee, Gen-Chi Lu, and Emery Jou, Movie Rating and Review Summarization in Mobile Environment, International Journal of Scientific and Research Publications, Volume 3, Issue 6, June 2013.
- [6] . Santhosh Kumar K L, Jayanti Desai, Jharna Majumdar, Opinion Mining and Sentiment Analysis on Online Customer Review, IEEE International Conference on Computational Intelligence and Computing Research 2016.
- [7] . Kajal Sarawgi, Vandana Pathak, Opinion Mining: Aspect Level Sentiment Analysis using SentiWordNet and Amazon Web Services, International Journal of Computer Applications (0975 8887) Volume 158 No 6, January 2017.

- [8] . Zheng-Jun Zha,, Jianxing Yu, Jinhui Tang, Meng Wang,, and Tat-Seng Chua, Product Aspect Ranking and Its Applications, IEEE Transactions On Knowledge And Data Engineering, VOL. 26, NO. 5, MAY 2014.
- [9] . V. Hatzivassiloglou and K. R. McKeown, Predicting the semantic orientation of adjectives, in Proc. 8th Conf. Eur. Chap. Assoc. Computer Linguist., Morristown, NJ: Assoc. Computer Linguist., pp. 174181, 1997.
- [10] 0. Haseena Rahmath P., Opinion Mining and Sentiment Analysis-Challenges and Applications, International Journal of Application or Innovation in Engineering Management, 2014
- [11] 1. Vamsee Krishna Kiran M, Vinodhini R E, Archanaa R and Vimalkumar K., User specific product recommendation and rating system by performing sentiment analysis on product reviews, 2017.