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Online Product Evaluation System Based on Ratings and Review

[1]Thugu Rajesh Kumar Reddy, [1]Chitra, [2]Jeyarani Periasamy

[1]Dayananda Sagar Academy of Technology and Management, Bangalore, India
[2]Faculty of Data Science and Information Technology, INTI International University, Malaysia

Email: rajeshkumarreddy34@gmail.com, chitra-mca@dsatm.edu.in

Abstract

The decision-making process for product design and improvement is hindered by traditional user research methods due to the rapid updating pace, limited survey scopes, small sample sizes, and labor-intensive procedures. This study suggests a novel method for gathering valuable online evaluations from e-commerce platforms, develops a system for measuring the effectiveness of a product and suggests ways to improve a product using sentiment analysis and opinion mining of online reviews. The method's efficacy is supported by a sizable body of user reviews for smartphones, from which we can reliably estimate the product's unfavorable review rate with only a 9.9% error using the assessment indication system. After considering the entire method in the case study, improvement strategies are suggested. The strategy is applicable for product evaluation.

Keywords

Sentiment Analysis, Feature Extraction, E-Commerce

Introduction

E-commerce has grown steadily as people's daily lives have become more integrated with the Internet Sullivan (Y. W., & Kim, D. J., 2018). People are making more purchases online and more things are being sold online. An increasing number of consumers post product reviews on retail websites to share their shopping experiences and feedback (Wolkenfelt, M. R. J., & Situmeang, F. B. I., 2020). They also express their thoughts and experiences in any network space, including blogs, discussion forums, and internet forums, which are rife with opinions about products.

Customers are finding it more and more challenging to make selections about what to buy based solely on product images and brief descriptions. Therefore, it is possible to rank each product based on the attributes that are automatically provided by user reviews to avoid confusion. An organized method of opinion mining is created via the work of numerous researchers, and Hu and

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Liu suggest one practical way, a feature-based opinion summary of reviews (Park, S., & Nicolau, J. L., 2015).

Structured summarization is a component of opinion mining; it is not about free material. It entails analyzing the product's features that customers have commented on and then ranking the features based on how frequently they appear in the reviews. Users frequently concentrate on the aspects of a product that users either like or dislike. The first step in opinion mining is extracting product features (Bleier, A., et. Al., 2019). Each review will identify opinion phrases for each feature and assess the semantic orientation of each one. The specific product reviews submitted by potential buyers are examined, and the results are condensed. acquired knowledge (Wolkenfelt, M. R. J., & Situmeang, F. B. I., 2020).

Prior rating systems often assign a product a quality score based on both its features and overall quality. A product often has several characteristics, each of which serves a distinct purpose. Different product attributes might pique the interest of various clients. Many consumers have historically relied on expert rankings, which only rate a small number of products. The links between items can be modeled by creating a weighted and directed graph using the data from customer reviews (Lăzăroiu, G., 2020).

One of the most persuasive methods of evaluation is comparison. Comparing "The display of Sony T200 is better than Canon G9" to "The display of Sony T200 is good" reveals different facts. The latter conveys a more insightful message regarding the Sony T200 camera. Additionally, customers frequently want to compare products at a very fine level of detail, such as the display of a digital camera or the battery life of a smartphone. A buyer can make decisions by carefully comparing the features of potential products before making a purchase. In this regard, product comparisons are crucial in online shopping (Zhu, L.,2020).

Researchers have focused on this issue using a variety of methods. By recognizing comparable sentences, Liu et al. compare two products. And discovering relationships between two things based on some shared characteristics. His techniques are capable of a fair amount of precision. It is challenging to compare any products on any attributes, nevertheless, as comparing words is uncommon in product reviews (Guo, J., Wang, X., & Wu, Y., 2020). A prototype system named "Opinion Observer", which focuses on examining and contrasting viewpoints on the web, is being implemented in Liu et al.'s other work.

The comparison results are visually shown by the system so that the user can easily perceive the advantages and disadvantages of each product in terms of numerous product attributes. But the measure of a feature's strength is as easy as measuring how many people have good and negative impressions of it. In truth, each opinion's sentimental strength is likewise quite strong. crucial when consumers share their product experiences. As opposed to the more common remark, "The display of Sony T200 is good," the phrase "The display of Sony T200 is very excellent" definitely contributes more positively to the "display" feature. Author reviews are rated on a multi-point system (such as one to five "stars") (Jebarajakirthy, C., & Shankar, A., 2021), to determine the strength of the opinions expressed. While he is unable to provide specific grades for each feature, his work only concentrates on the document level.

Our work has progressed further; we now give a comprehensive review of every feature of a product, considering the technical specifications of the product, in addition to taking into account the strength of each customer's opinion. Results of comparisons based on the evaluation of each feature have attained excellent precision.

Methodology

Agile Methodology

The agile methodology is a style of project management that breaks projects into smaller, more manageable chunks known as "sprints." Continuous communication and collaboration between all the different actors are required for continuous improvement at every level. As soon as they start working, teams immediately start a process that comprises planning, carrying out, and evaluating the work that they have done (Xiong, X, et.al., 2020).

To guarantee success, ongoing communication between team members and people who have a personal stake in the project is necessary. The term "agile project management" refers to a form of project administration that emphasizes collaborative efforts and incremental progress. The idea that it is feasible to make incremental improvements to a project throughout its lifetime by adjusting as needed is at the heart of the agile project management approach (Ngarmwongnoi, C, 2020).

This concept serves as the foundation for the agile software development process. Agile project management is rapidly becoming one of the most popular approaches to the management of projects. The success of agile project management can be attributed, in large part, to the adaptability, high client involvement, and openness to change that characterizes agile project management How is the Scrum technique different from other approaches, and what are those ways? An approach that is heuristic places a primary emphasis on gaining knowledge via experience and modifying behaviors in response to shifting conditions.

Heuristic frameworks are built based on experience and experimentation; Scrum is one such framework. It acknowledges the fact that the team can't possibly know everything at the beginning of a project and that they will discover new things as they move forward in the process of completing the task at hand. The purpose of Scrum is to make it possible for teams to more readily change their processes to fulfill ever-evolving requirements and a growing range of expectations. Your team will be able to consistently learn new things and get better if you incorporate reprioritization and keep release cycles as short as possible. There are three fundamental aspects of a scrum team that will never lose their significance and will continue to always deserve our utmost commitment and effort.

The Product Backlog, the most important list of tasks that need to be completed, is managed by either the product owner or the product manager, depending on who is in charge of the product. This ever-evolving collection of features, requirements, enhancements, and bug fixes serves as the input for the sprint backlog. The "To Do" list of a team is, in its most basic form, a compilation of items that fit that criterion. The Sprint Backlog is a prioritized list of features, user stories, or bug patches that the development team has decided to concentrate on during the current sprint. This list may be found in the product's sprint planning document. The team has evaluated the following components, established their relative significance, and ranked them as such. In the meeting known as "sprint planning," which takes place right before each sprint, the team decides which items from the product backlog they will work on during that sprint.

An increment is the term used to refer to the result of a sprint that has been finished and is ready to be used. A sprint target is another name for an increment. You might not hear the term "increment" very often because it is more common to talk about "Done" in terms of the team's definition, a milestone, the sprint objective, or even a complete version or a deployed epic. As a result, the term "increment" is less likely to be used. Both the meaning of the term "Done" and the organization of your sprint's goals are quite important.

Data flow diagram

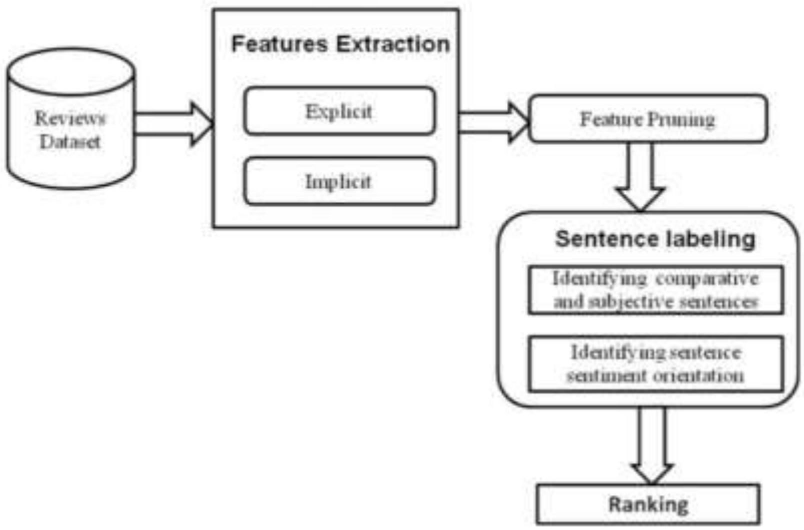

Figure 1. Data Flow Diagram of the Labeling

Results

In this section, we apply the suggested methodology to a case study on the smartphone with online user evaluations and talk about the findings for the three key research questions. For the section's organization, we first describe the review datasets that were employed, followed by a discussion of the research topics.

Data Collection and Preprocessing

In China, Jingdong (JD.com) and Taobao (taobao.com) are the most well-known E-commerce platforms. As Jingdong adopts a B2C model, there is less internal competition than Taobao—a

C2C (Consumer to Consumer) platform. Thus, Jingdong has fewer fake reviews, and the data is more reliable for analysis.

We crawl a total of 1,257,482 online reviews from the top 60 best-selling smartphones. To ensure the accuracy of review data, we preprocess the crawled reviews by deleting duplicated reviews, reviews containing advertisements, and reviews with punctuation marks, and, finally, get 1,189,357 reviews.

Results for Useful Review Acquisition

We start by looking into the smartphone's product features. We raise K incrementally to establish the K parameter of the LDA and discover that (1) similarity falls with K when K is less than 18 and (2) grows with K when K is larger than 18. As a result, when K is equal to 18, there is the least resemblance between the product features.

Since K is set to 18, the LDA outputs yield 18 topics, each of which represents a different product attribute. Three of them, though, are made up entirely of verbs, adverbs, and adjectives. These three topics were manually eliminated since they are unable to describe product qualities.

Conclusion

Interviews and questionnaires are commonly used in traditional product design to gather consumer feedback. This results in a longer design cycle, but these survey methodologies require more time, have a smaller survey scope, and cost more to conduct. The emergence of the big data era has given rise to a fresh concept for mining customer reviews to improve products. Big data analysis and sentiment analysis help designers better understand user demands and make decisions. To enhance product improvement, this study suggests a system of product evaluation indicators that combines big data analysis and sentiment analysis.

The suggested method may produce a thorough and verified evaluation of the product indicators based on big data, obtain more user input in less time, track user preferences more successfully, and identify. Enhance review analysis automation to make it easier to quickly transfer the process to other products. Consider the trade-offs between computing for user opinions, innovation, and cost. Use actual production practices to test the techniques by implementing the improvement initiatives.

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