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Product Recommender System Based on Ranking and Customers Reviews Using PRUS Algorithm

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ABSTRACT

Customers now have a bewildering array of options due to the quick expansion of e-commerce, making it challenging to choose the finest products based on individual preferences. Purchase decisions are heavily influenced by customer evaluations and ratings, yet current recommendation algorithms frequently fall short in taking into account both positive and negative opinions. A sentiment-aware ranking system is used in this project's proposed Product Recommender System Based on Ranking and Customer Reviews (PRUS) to prioritize products. The system gathers user feedback, analyzes the sentiment of each product feature using Aspect-Based Sentiment Analysis (ABSA), and gives each product a weighted rank score based on a number of factors, including review polarity, frequency, and recency. To improve accuracy and personalization, a hybrid recommendation strategy that combines content-based and collaborative filtering is employed. Metrics like Normalized Discounted Cumulative Gain (nDCG), Precision, Recall, and F1-score are used to assess the system's efficacy and guarantee dependable and user-focused recommendations. By enabling consumers to select recommendations based on particular product qualities, the suggested method offers a very customizable and tailored purchasing experience, thereby improving making choices in online retail settings.

Keywords: *Product Recommender System,Ranking Mechanism, Customer Reviews, Sentiment Analysis, Aspect-Based Sentiment Analysis (ABSA), Collaborative Filtering, Content-Based Filtering, Normalized Discounted Cumulative Gain (nDCG), Machine Learning, E-commerce Recommendations.*

I. INTRODUCTION

The way consumers make decisions about what to buy has changed as a result of e-commerce's explosive growth. Selecting the ideal product has grown more difficult with millions of options available online. Because they offer information about other purchasers' experiences, customer reviews and ratings are extremely important in influencing judgments about what to buy. However, people may find it hard to manually analyze the large number of evaluations created every day in order to determine which product is best. By using sentiment analysis and ranking algorithms to offer tailored product recommendations, a product recommender system based on rating and customer reviews aims to streamline this procedure.

The precise sentiments conveyed in textual reviews are frequently ignored by traditional recommender systems, which mainly concentrate on numerical ratings. Certain methods combine evaluations to obtain a general attitude, but they are unable to discern between favorable and unfavorable opinions for certain features of the product (such as camera quality or battery life). This restriction may result in recommendations that are deceptive because even a product with a high average rating may receive unfavorable reviews on important features that are important to certain consumers. In order to overcome this difficulty and provide a more accurate assessment of consumer input, the suggested approach employs Aspect-Based Sentiment Analysis (ABSA) to gather thoughts on particular product attributes.

A weighted ranking technique that takes into account a number of variables, such as sentiment polarity, the number of reviews, recency, and overall ratings, is used by the algorithm to rank products. The recommendation system tailors product recommendations according to user preferences and previous interactions by combining collaborative filtering with content-based filtering. Users can also choose which product attributes are most important to them, making their purchasing experience more personalized.

By offering clear and feature-specific insights, this research attempts to create a scalable and effective recommender system that not only increases recommendation accuracy but also boosts user confidence. Key performance indicators including Normalized Discounted Cumulative Gain (nDCG), Precision, Recall, and F1-score are used to assess the system's performance and guarantee the efficacy and dependability of the suggestions. The suggested solution seeks to improve the online shopping experience by bridging the gap between product offerings and customer expectations.

II. LITERATURE STUDY

System analysis will be carried out to identify the weaknesses of the current system and to ascertain whether it is flexible enough to develop information based on organizational policies and strategies as well as user requirements. The current system, the suggested system, and the salient features of the system needs are covered in this chapter.

According to Dimoka et al., there are more detrimental repercussions from high product uncertainty than from high seller uncertainty. Kim and Krishnan observed that even if customers have a lot of experience buying online, they are unwilling to purchase pricey products (defined as those costing more than $50) if there is a significant level of product uncertainty. E-commerce businesses have therefore tried to reduce product confusion in a number of ways, including by offering thorough descriptions, using multimedia and virtual reality capabilities, and—most importantly—asking for customer feedback.

Khare et al. discovered that consumer judgment is fundamentally impacted by the quantity and degree of consensus of reviews. Therefore, both of these variables must be taken into consideration in an effective review solicitation strategy. Users are usually asked to write a free-text evaluation on existing e-commerce sites. The general opinion of reviewers for each feature of a product can then be estimated by analyzing these reviews using feature and sentiment extraction techniques. Other websites ask users to rate a static (predefined) list of factors, usually assigning a number between 1 and 5. For instance, "How clean was your room?" or "How reliable do you think the car is?"

DRAWBACKS

● The fact that certain parts acquire excessive ratings is a major flaw in the current review soliciting methods. This is particularly inefficient if reviewers are frequently in agreement with one another. For instance, take the "smartphone" product, which has features like "screen," "battery," "design," and so forth.

Hundreds of reviews might give the "screen" five stars. A more contentious feature, like the "speed," on the other hand, might only get a few ratings. Because people tend to utilize evaluations from previous users to compare different items across multiple characteristics (features), this results in a review profile with a high degree of uncertainty.

III. DEVELOPMENT OF PRODUCT RECOMMENDER SYSTEM BASED ON RANKING AND CUSTOMERS REVIEWS

Based on user reviews, a number of previous studies have graded products according to user specifications; nevertheless, the majority of these research have only emphasized the positive elements. The current study aims to provide an efficient method for choosing and ranking products based on user requirements by taking into account both the positive and negative feelings associated with these factors.

The main contributions of the study are enlisted below:

A product list based on user-specified features was extracted from the review dataset using the Product Recommendation based on User Specification (PRUS) framework.

By separating the sentiment of each aspect from the sentiment of the review as a whole, a method for assigning feelings to the aspects or features was proposed.

● Created a process to give weights to the aspects' positive and negative sentiment counts in order to produce a list of suggested products based on the polarity of each aspect, either positive or negative.

Using the review dataset, a thorough experimental evaluation was conducted to determine the efficacy of the suggested PRUS method.

ADVANTAGES:

● It provides a high degree of customization for the suggestions.

● It can accommodate a larger number of people.

● It has the ability to suggest things to users with unusual interests.

● It provides a high level of security against the creation of harmful items and lets users stop viral marketing.

Adaptable and appropriate for a range of fields.

● No need to examine the contents of the products.

● It offers a high level of personalization in the recommendations.

● It is scalable in terms of the number of users.

● It can make recommendations for users with peculiar interests.

● It has high security from malicious item creation and allows users to prevent viral marketing.

● Flexible and suitable for various domains.

● No need to analyze the items' contents.

Modeling Design:

The preparation of the data for use in the following two stages is the main goal of this phase. The first scenario involves creating a rating matrix with users as rows and items as columns. The value of each matrix cell represents the user's rating of a particular item. The second step is creating a user profile, which is essentially a vector for every user that describes his preferences for a product in its entirety or for certain features. The third step is creating an item model that incorporates the characteristics of a particular object.

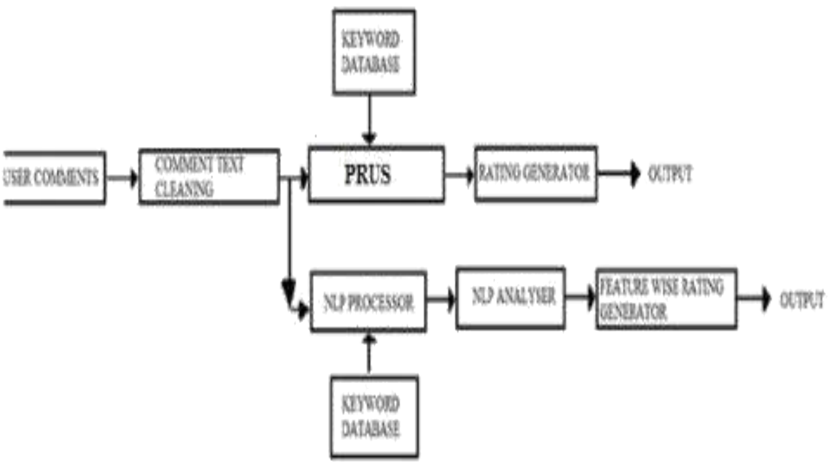
Prediction Phase:

Using a utility function based on the data retrieved during the modeling phase, this phase seeks to forecast the rating or score of unknown or unseen objects for a particular user.

Recommendation Phase:

The recommendation phase, which is an extension of the prediction phase, uses a variety of strategies to help the user make a selection by sifting through the best options. It suggests new terms that the user is likely to find interesting (i.e., a list of the top-N items with the highest expected ratings).

ARCHITECTURAL DIAGRAM



IV. RESULT AND DISCUSSION

In the implementation phase, the engineer's efforts to develop the system are the main focus. The organization of data, the implementation of procedural details, the characterization of interfaces, the translation of design into programming, and testing are all covered. There should always be three distinct technical jobs during the development phase, regardless of the methodologies used.

● The software design

● Code generation

● Software testing

The creation of code and software testingThe task of designing and developing a new information system as well as creating a new system to satisfy requirements has been transferred to the system group. Numerous users at all organizational levels served as the source of these study facts.

Stage of Development of a System

● Feasibility assessment

● Requirement analysis

● External assessment

● Architectural design

- Detailed design
- Coding
- Debugging
- Maintenance

Feasibility Assessment

This level problem was defined in Feasibility. They created criteria for selecting a solution, suggested potential solutions, calculated the system's costs and benefits, and suggested a course of action.

Requirement Analysis

High-level needs, such as the system's capabilities, must be supplied during requirement analysis in order to address an issue.

In order to characterize the elements that the proposed system will integrate, function requirements and performance requirements for the hardware specified during the initial planning were expanded upon and made more precise.

External Design

Any software development's external design entails identifying, organizing, and defining the features that the software product will be able to see from the outside. User displays, report formats, external data sources, data connections, and functional features are some examples of these attributes.

Internal Design Architectural and Detailed Design

In order to document the design choices and be able to explain why some changes were preferred over others, internal design required conceptualizing, planning, and defining the internal structure and processing details. These stages also offer blueprints for implementation, testing, and maintenance tasks, as well as the development of test plans. Architectural structural specifications are the end result of internal design.

The specifications for the architectural structure, algorithmic details, data structure, and test plan are the end products of internal design. The conceptual view is refined in architectural design.

Detailed Design

Detailed design entailed defining the algorithmic specifics related to data representation, data structure linkages, and software product packaging. This stage places less emphasis on artificial details and more on semantic concerns.

Coding

Actual programming, or converting a comprehensive design into source code using the proper programming language, is what this phase entails.

Debugging

This phase dealt with eliminating errors from programs and ensuring that they were error-free.

Maintenance

During this stage the systems are loaded and put into use. They also get modified according to the requirements of the user. These modifications included making enhancements to the system and removing problems.

V. CONCLUSION AND FUTURE

ENHANCEMENT

Presently, user-generated reviews are utilized to increase the PRUS performance's accuracy by converting the unstructured user reviews into a structured format that can be combined with RSs through the usage of text and sentiment analysis. The issue of incorrect recommendations brought on by depending solely on the overall ratings in the recommendation process can be resolved by extracting numerous components from user reviews and then sending them to the RSs' methods. Because using the PRUS seems to improve performance, this work focuses on the PRUS that extracts their criteria from user reviews. Image ratings and reviews from users are successfully incorporated and carried out. After that, the methods that incorporate these components into the PRUS are described and categorized according to the review components that were employed to create their systems.

SCOPE FOR FUTURE ENHANCEMENT

Finally, some of the future trends are discussed as challenges or open problems for this type of PRUS. We expect this work will help researchers to gain more understanding about the multi-criteria review based recommender system and encourage them to explore the implicit values of the reviews and utilize them in future studies.

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