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Product Recommendation Mining Based in User Interested and Rating Prediction on Textual Reviews

J. Niranjan[1*], S. Shanmugavel[2], T. S. R. Balakumaran[3], S. J. Vivekanandhan[4]
[1,2,3]*Bachelor of Engineering, Department of Computer Science and Engineering, Dhanalakshmi College of Engineering, Chennai, India*
[4]*Assistant Professor, Department of Computer Science and Engineering, Dhanalakshmi College of Engineering, Chennai, India*

***Abstract*: Any modern internet shopping or social networking plan supports a recommendation mechanism. As an example of outdated recommendation systems, the content - based recommendation system has two key flaws: suggestion redundancy and unpredictability when it comes to new things (cold start). The user's social characteristics, such as personality characteristics and topical interest, may be able to reduce the cold start and eliminate redundant recommendations. Even if the user's history doesn't really contain these or similar items, Meta-Interest predicts the user's interest and the objects linked with these interests. In two ways, the developed scheme is personality-aware: it uses the user's personality features to forecast his or her themes of interest and to link the user's personality facets to the associated items. The proposed system was compared against Recent suggestion systems, such like deep-learning-based recommendation systems and session-based recommendation systems, were compared to the suggested system. In this paper, we present a sentiment-based suggestion strategy (RPS) to increase recommender system prediction accuracy. To enhance predictive performance in recommender systems, we present a sentiment-based rating prediction strategy (RPS) in this paper. To achieve an accurate rating prediction, we combine three criteria into our recommender system: user sentiment resemblance, social sympathetic influence, and item reputation similarity. Sentiment analysis can be carried out at three different levels: review, sentence, and phrase. Analysis at the review level. Our findings suggest that sentiment can accurately describe user preferences, which aids in improving recommendation performance.**

***Keywords*: Sentimental analysis, data mining, product recommendation, feedback, mining, textual reviews.**

1. Introduction

Recommendation is the methodology of suggesting or proposing something as the best or most suitable for a specific customer. In this project, we will discuss how to recommend a product using customer ratings and feedback. There are a large variety of products that are available, and because technology is at its core, there are multiple products over the internet, so proposing a quality product will be difficult, but by evaluating the data provided by users, such as ratings and feedback, we can make suggestions with high accuracy. The most essential element introduced to our project is Emotional analysis, which aids in boosting ranking accuracy of the product.

The proposed system compared against latest recommendation approaches, such like deep-learning-based recommendation systems and session-based recommendation systems, were compared to the suggested system. In this paper, we present a sentiment-based rating prediction strategy (RPS) to increase recommender system prediction accuracy.

2. Existing System

The necessity of incorporating the user's personality attributes into recommendation systems has been highlighted in numerous works. Yang et al. [4] suggested a computer game recommendation system for users based on personality attributes. They used text mining techniques to assess the players' huge personality traits and then categorised a list of games based on how well they fitted each trait. A product suggestion system based on the user's topical interests that infers the user's needs. presented a CF system that uses the K-means algorithm to cluster people based on their huge personality traits. Following that, the clustered users are used to predict unknown rating of the limited user–item matrix. The authors examined all prior publications in the field on user interest mining via social networks, stressing the following four features.

1) data gathering;
2) user interest profile representation;
3) user interest profile construction and refining; and
4) user interest profile evaluation measures.

Meta-goal Interest's is to offer a most relevant items to a user by recognising their thematic interests from their social networking data. the measurement of personality qualities, which can be collected by requesting the user to complete a personality measuring questionnaire or by analysing the subject's social network data using automatic personality identification. Because personality qualities have been shown to be rather constant over time, the personality measuring portion is the only static portion of the system. Step 2 involves mining the user's thematic interests, both explicitly and implicitly. The text provided by the user is analysed for explicit interest mining. Big-five is used to model the user's personality

*Corresponding author: jssn2niranjan@gmail.com

in the suggested system. A potential direction is to extend Meta-Interest to include all personality attribute model, such as Myers–Briggs type indicator.

Disadvantages:

- The product recommendation system as an example of outdated recommendation systems, the product recommendation system has two key flaws: suggestion redundancy and unpredictability when it comes to new things.
- These limitations arise because traditional recommendation systems rely solely on the user's previous purchasing activity to make.
- The current system focuses primarily on the user who is interested in mining, not the other way around. Refers to the user feedback in the mining industry.
- One of the most difficult aspects of HIN link prediction is striking a good balance between the amount of data used to make the forecast and the computational complexity of the strategies used to acquire it.
- The existing system does not incorporate sentiment analysis or level-based analysis.

Advantages:

- The suggested system was compared to newer recommendation approaches, such as deep-learning-based and session-based recommender system.
- Proposed a friend recommendation system based on the Big Five personality factors theory and hybrid filtering.
- We make use of sentiment for rating prediction. User For rating prediction, we use sentiment. User sentiment similarity is concerned with the user's interests. The diffusion of sentiment among trusted users is measured by user sentiment influence.
- Item reputation similarity reveals the items' probable importance.
- To provide an accurate suggestion, we combine the three components of user sentiment matching, interpersonal sentimental impact, and product reputation resemblance into a probabilistic data augmentation framework.
- We investigate not just social user sentiment, but also interpersonal sentimental effect and item reputation in our work. Finally, we enter them all into the recommendation system.

3. Proposed System

To enhance predictive performance in recommender systems, we present a sentiment-based rating prediction strategy (RPS). To begin, we suggest a social user sentiment measurement method, in which we calculate each user's sentiment toward items/products. Second, we take into account not only a user's own sentimental traits, but also interpersonal sentimental influence. Then there's item reputation, which can be deduced from the sentimental patterns of a user set, which indicate customers' overall assessment. Finally, we include three criteria into our recommender system to generate an accurate rating prediction: user sentiment resemblance, interpersonal sentimental influence, & product reputation similarity. It combines the user's personality qualities to predict his/her themes of interest and to link the user's personal facets with the related things, making it personality-aware in two ways. Our findings suggest that sentiment can accurately describe user preferences, which can help to improve recommendation performance. The goal of review-level and sentence-level analysis is to categorize the sentiment of an entire review into one of the established sentiment polarities, which include positive, negative, and neutral. Latest recommendation techniques, like deep-learning-based recommendation and session-based recommendation systems, were compared to the suggested system.

4. Results

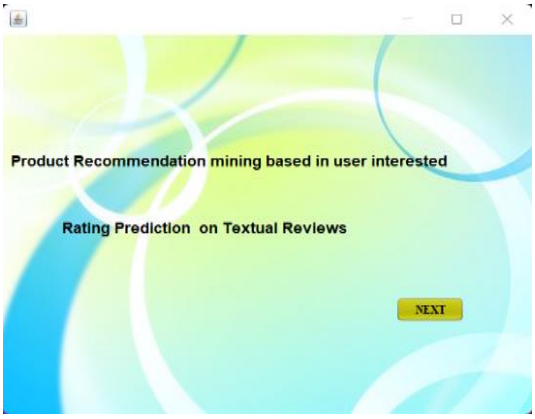

Fig. 1. Home page

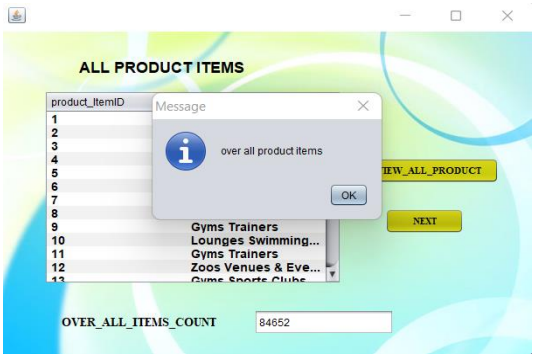

Fig. 2. All products

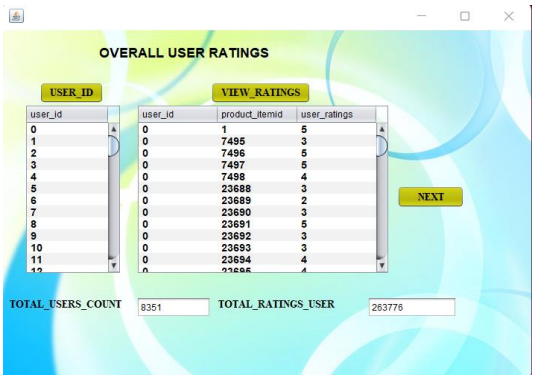

Fig. 3. Overall user ratings

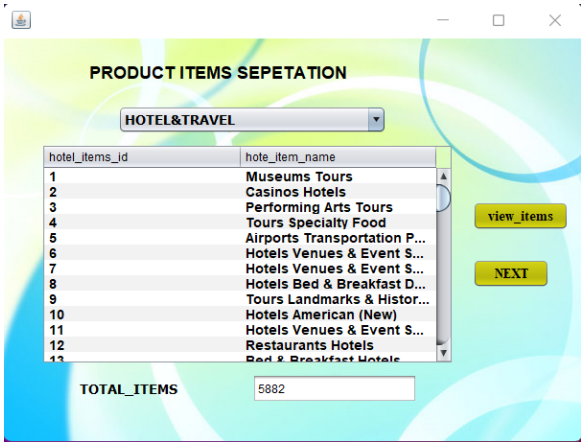

Fig. 4. Product items separation

Fig. 5. Items based on user's

Fig. 6. Interpersonal user sentiment

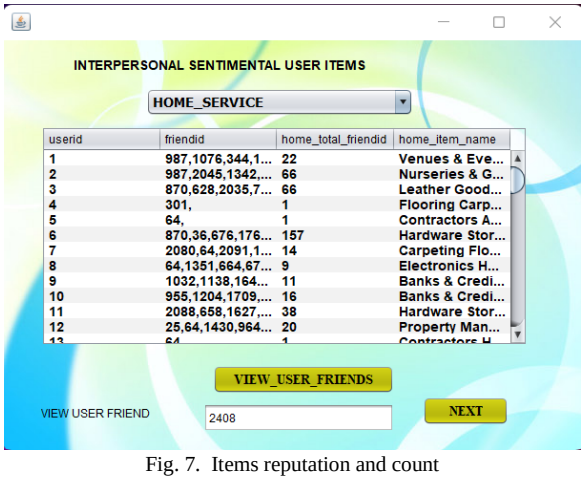

Fig. 7. Items reputation and count

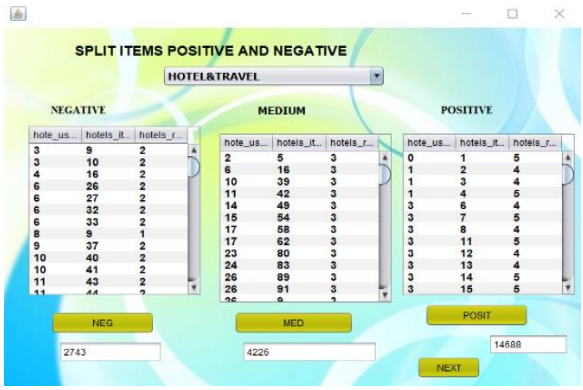

Fig. 8. Sentimental analysis

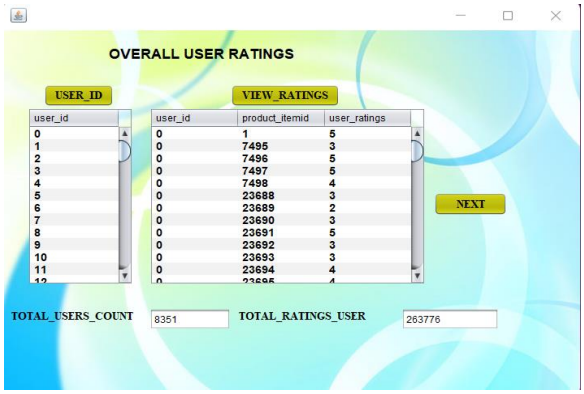

Fig. 9. Overall user rating and feedback

5. Conclusion

The suggested system is personality-aware in two ways: first, it uses the user's personality features to forecast his interests, and second, it connects the user's personality facets to the linked items. Questionnaires were used to assess the personality attributes of the consumers. Including an automatic personality detection method that can recognize individuals' personality attributes based on shared data to complete the rating prediction challenge, we combine user sentiment similarities, interpersonal sentiment impact, and product reputational similarity into a unified factorization framework. Furthermore, as long as we have user textual reviews, we can quantitatively assess user sentiment, and we can infer item reputation based on item sentiment distribution among users. To use fine-grained sentiment analysis, we can improve the sentiment dictionaries. The building of a sentiment lexicon is the primary goal of phrase-level sentiment analysis. Pang et al. present an evaluative lexical technique that is context agnostic. To combine phrase-level sentiment analysis, we can also adapt or construct additional hybrid factorization models, like tensor factoring or deep learning techniques.

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