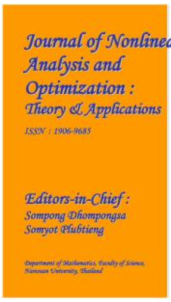
Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 14, Issue. 2, 2023
ISSN : **1906-9685**



PERSONALITY AWARE PRODUCT RECOMMENDATION SYSTEM BASED ON USER INTEREST MINING AND METAPATH DISCOVERY

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ABSTRACT

In the context of epidemic prevention and control, food safety monitoring, data analysis and food safety traceability have become more important. At the same time, the most important reason for food safety issues is incomplete, opaque, and asymmetric information. The most fundamental way to solve these problems is to do a good job of traceability, and establish a reasonable and reliable food safety traceability system. The traceability system is currently an important means to ensure food quality and safety and solve the crisis of trust between consumers and the market. Research on food safety traceability systems based on big data, artificial intelligence and the Internet of Things provides ideas and methods to solve the problems of low credibility and difficult data storage in the application of traditional traceability systems. Therefore, this research takes rice as an example and proposes a food safety traceability system based on RFID two dimensional code technology and big data storage technology in the Internet of Things. This article applies RFID technology to the entire system by analysing the requirements of the system, designing the system database and database tables, encoding the two- dimensional code and generating the design for information entry. Using RFID radio frequency technology and the data storage function in big data to obtain information in the food production process. Finally, the whole process of food production information can be traced through the design of dynamic query platform and mobile terminal. In this research, the food safety traceability system based on big data and the Internet of Things guarantees the integrity, reliability and safety of traceability information from a technical level. This is an effective solution for enhancing the credibility of traceability information, ensuring the integrity of information, and optimizing the data storage structure.

I. INTRODUCTION

With the widespread of personal mobile devices and the ubiquitous access to the internet, the global number of digital buyers is expected to reach 2.14 billion people within the next few years, which accounts for one fourth of the world population. With such a huge number of buyers and the wide variety of available products, the efficiency of an online store is measured by their ability to match the right user with the right product, here comes the usefulness of a product recommendation systems. Generally speaking, product recommendation systems are divided into two main classes: (1) Collaborative filtering (CF), CF systems recommend new products to a given user based on his/her previous (rating/viewing/buying) history Sahraoui Dhelim, Huansheng Ning and Nyothiri Aung are with School of Computer and Communication Engineering, University of Science and Technology Beijing, 100083, Beijing, China. Runhe Huang and Jianhua Ma are with the Faculty of Computer and Information Sciences Hosei University, Japan. Corresponding author: Huansheng Nin(ninghuansheng@ustb.edu.cn). Manuscript received September 24, 2019; revised October 03, 2020. and his/her neighbours. For example, as shown in Figure 1 (a), most of the people of previously bought a football jersey, they have also bought a football, thus the system predicate that the user might be interested in buying a football. (2) Content filtering or content-based filtering (CBF). CBF systems recommend new items by measuring their similarity with the previously (rated/viewed/bought) products. For example, as shown in Figure 1 (b), the football is recommended because semantically similar to the football jersey.

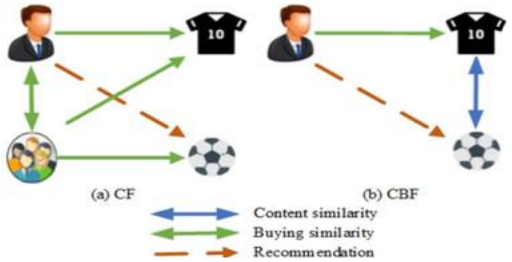

Fig.1.1: Collaborative filtering and content filtering

Far from that, with the popularity of online social networks such as Facebook, Twitter and Instagram, many users use social media to express their feeling or opinions about different topics, or even explicitly expressing their desire to buy a specific product in some cases. Which made social media content a rich resource to understand the users' needs and interests [1]. On the other hand, the emerging of personality computing [2] has offered new opportunities to improve the efficiency of user modelling in general and particularly recommendation systems by incorporating the user's personality traits in the recommendation process. In this work, we propose a product recommendation system that predicts the user's needs and the associated items, even if his history does not contain these items or similar ones. This is done by analyzing the user's topical interest, and eventually recommend the items associated with the theses interest. The proposed system is personality-aware from two aspects; it incorporates the user's personality traits to predict his topics of interest, and to match the user's personality facets with the associated items. As shown in Figure 2 the proposed system is based on hybrid and filtering approach (CF and CBF) personality-aware interest mining.

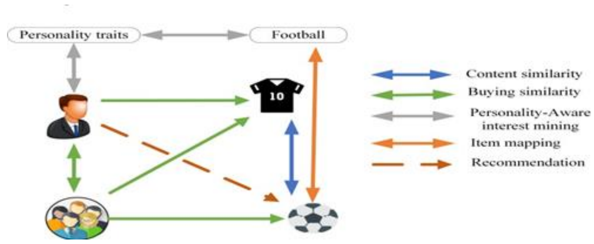

Fig. 1.2: Interest mining based product recommendations

Since we have multiple types of nodes (users, items and topics), the system is modelled as a heterogeneous information network (HIN), which includes multiple types of nodes and links. In our case, product recommendation could be formulated as link prediction in HIN [3]. For example, in Figure 2, given the user's previous rating and topical interest represented in a HIN, the problem is to predict whether or not a link exists between the user and the product (the ball). One of the main challenges of link prediction in HIN is how to maintain a reasonable balance between the size of information considered to make the prediction and the algorithm complexity of the techniques required to collect that information. Since in practice, the networks are usually composed out of hundreds of thousands or even millions of nodes, the method used to perform link prediction in HIN must be highly efficient. However, computing only local information could lead to poor predictions, especially in very sparse networks. Therefore, in our approach, we make use of meta-paths that start from user nodes and end up in the predicted node (product nodes in our case), and try to fuse the information from these meta-paths to make the prediction. The contributions of this work are summarized as follows: 1) Propose a product recommendation system that infers the user's needs based on her/his topical interests. 2) The proposed system incorporates the user's Big-Five personality traits to enhance the interest mining process, as well as to perform personality-aware product filtering. 3) The relationship between the users and products is predicted using a graph-based meta path discovery, therefore the system can predict implicit as well as explicit interests. The remainder of this paper is organized as follows. In Section 2 we review the related works, while in Section 3 the system design of the proposed system is presented. In Section 4 we evaluate the proposed system. Finally, in Section 5 we conclude the work and state some of the future directions.

1.1 Scope:

The scope of our Personality-Aware Product Recommendation System spans the intersection of user psychology, interest mining, and metapath discovery. We aim to analyze user preferences, behaviours, and interactions to unearth valuable insights into individual personalities. By employing advanced algorithms for metapath discovery, we connect the dots between diverse product categories, ensuring holistic and context-aware recommendations. The system's scope encompasses not just product suggestions, but a comprehensive understanding of users' evolving tastes, ultimately shaping a dynamic and highly personalized shopping journey.

1.2 Purpose:

The purpose of our Personality-Aware Product Recommendation System is to revolutionize the online shopping experience. By leveraging user interest mining and metapath discovery, our system aims to achieve the following:

1.2.1 Personalization:

Tailor recommendations based on users' unique personalities and evolving interests, ensuring a more engaging and relevant shopping experience.

1.2.2 Enhanced User Understanding:

Gain deeper insights into user preferences, behaviours, and connections between different product categories through metapath discovery, allowing for a comprehensive understanding of individual tastes.

1.2.3 Dynamic Adaptability:

Continuously adapt to users changing preferences by employing advanced algorithms that analyse metapaths, ensuring recommendations stay relevant over time.

1.2.4 Improved Engagement:

Foster increased user engagement and satisfaction by offering personalized suggestions that align not only with explicit preferences but also with the subtleties of individual personalities.

1.2.5 Cross-Category Recommendations:

Explore connections between seemingly disparate product categories, providing users with serendipitous discoveries and expanding their shopping horizons.

In essence, our system aspires to redefine how users discover and interact with products, making the online shopping experience not just efficient but an enjoyable journey reflective of their unique tastes and personalities.

1.3 Objective:

The primary objectives of our Personality-Aware Product Recommendation System, driven by user interest mining and metapath discovery, include:

Precision in Recommendations: Develop algorithms that accurately mine user interests and preferences, ensuring precise and relevant product recommendations tailored to individual personalities.

1.3.1 Dynamic User Profiling:

Implement a robust system for continuously updating and refining user profiles, incorporating real-time changes in preferences through effective metapath discovery.

1.3.2 Enhanced User Experience:

Elevate the overall shopping experience by providing users with recommendations that not only align with their explicit preferences but also consider subtle nuances in their personalities, fostering a deeper connection.

1.3.3 Adaptability and Evolution:

Build a system that adapts to evolving user preferences over time, utilizing metapath discovery to understand the evolving relationships between different product categories and user interests.

1.3.4 Interdisciplinary Connections:

Explore metapaths to identify connections between diverse product categories, offering users serendipitous and cross-category recommendations that go beyond traditional silos.

1.3.5 User Engagement:

Increase user engagement by delivering recommendations that capture user attention, leading to a more satisfying and enjoyable shopping journey.

1.3.6 Algorithmic Transparency:

Ensure transparency in the recommendation process, allowing users to understand how their preferences are analysed and how recommendations are generated based on metapath discovery and interest mining.

By focusing on these objectives, our system aims to create a transformative and highly personalized online shopping environment that caters to the unique personalities and evolving preferences of each user.

II. LITERATURE SURVEY

In this section, we review the recent advances of personality aware recommendation system and interest mining schemes as well. A. Personality and recommendation systems Many works have discussed the importance of incorporating the user's personality traits in the recommendation systems. Yang et al. [4] proposed a recommendation system of computer games to players based on their personality traits. They have applied text mining techniques to measure the players' Big-five personality traits, and classified a list of games according to their matching with each dominant trait. They have tested their proposed system on 2050 games and 63 players form Steam gaming network. While Wu et al. [5] presented a personality based greedy re-ranking algorithm that generates the recommended list, where the personality is used to estimate the users' diversity preferences. Ning et al. [6] proposed a friend recommendation system that incorporates the Big-five personality traits model and hybrid filtering, where the friend recommended process is based on personality traits and the users' harmony rating. Ferwerda et al. [7] studied the relationship between the user's personality traits and music genre preferences, they have analysed a dataset that contains personality test scores and music listening histories of 1415 Last.fm users. Similarly in [8] they conducted an online user survey where the participants were asked to interact with an application named Tune- A-Find, and measured taxonomy choice (i.e. activity, mood, or genre), individual differences (e.g. music expertise factors and personality traits), and different user experience factors. Similarly, Hafshejani et al. [9] proposed a collaborative filtering system that cluster the users based on their Big-Five personality traits using K-means algorithm. Following that, the unknown ratings of the sparse user-item matrix are estimated based on the clustered users. Dhelim et al. [10] discussed the benefits of capturing the user's social feature such as personality traits that are represented as a cyber entities in the cyberspace. Similarly, Khelloufi et al. [11] showed the advantages of leveraging the user's social features in the context of service recommendation in the Social Internet of Things (Slot). B. Interest mining Far from personality, many previous works have discussed user interest mining from social media content. Piao et al. [1] surveyed the literature of user interest mining from social networks, the authors reviewed all the previous works by emphasizing the following on four aspects, (1) data collection,

(2) representation of user interest profiles, (3) construction and refinement of user interest profiles, and (4) the evaluation measures of the constructed profiles. Zarrinkalam et al.

[12] presented a graph-based link prediction scheme that operates over a representation model built from three categories of information: user explicit and implicit contributions to topics, relationships between users, and the similarity among topics. Trikha et al. [13] investigated the possibility of predicting the users' implicit interests based on only topic matching using frequent pattern mining without considering the semantic similarities of the topics. While Wang et al. [14] proposed a regularization framework based on the relation bipartite graph, that can be constructed from any kind of relationships, they evaluated the proposed system from social networks that were built from retweeting relationships. In [15], the authors discussed the usage of user's interests to customize the services offered by a cyber-enabled smart home. Faralli et al. [16] proposed Taxionomy, a method for modelling of Twitter users by a hierarchical representation based on their interests. Twiconomy is built by identifying topical friends (a friend represents an interest instead of social relationship) and associate each of these users with a page on Wikipedia. Dhelim et al. [17] used social media analysis to extract the user's topical interest. Kang et al. [18] proposed a user modelling framework that maps the user' posted content in social media into the associated

category in the news media platforms, and based on they used Wikipedia as a knowledge base to construct a rich user profile that represents the user' interests. Liu et al. [19] introduced iExpand, a new collaborative filtering recommendation system based on user interest expansion via personalized ranking. iExpand uses a three layer, user-interests-item, representation scheme, which makes the recommendation more accurate and with less computation cost and helps the understanding of the interactions among users, items, and user interests. Table I shows a comparison between the proposed system and some of the related works presented above. Some works such as metapath2vec [20], Shi et al. [21] have used metapaths embedding to represent the network information in lower dimensions for easy manipulation of heterogeneous graphs. However, in highly dynamic graphs such as the user-topic product graph in our case, where the graph update happens very frequently, computing the meta- path embedding all over again is very expensive in terms of computation.

2.1 Existing System:

Existing systems typically incorporated collaborative filtering, content based filtering, or hybrid approaches for recommendations. Advanced systems considered user behaviours, historical data, and preferences, but incorporating explicit personality traits and metapath discovery was a more cutting-edge direction.

2.2 Proposed System:

In our proposed Personality-Aware Product Recommendation System, we envision a comprehensive framework that seamlessly integrates user interest mining and metapath discovery for a highly personalized and adaptive shopping experience:

2.2.1 User Profiling and Personality Mapping:

Develop a robust user profiling mechanism to capture explicit preferences, purchase history, and demographic information. Incorporate personality indicators through user surveys, psychographic data analysis, or leveraging existing behavioural data.

2.2.2 Interest Mining Algorithms:

Implement state-of-the-art machine learning algorithms to mine implicit and explicit user interests from diverse data sources, including browsing behaviour, search history, and social interactions. Integrate sentiment analysis to gauge user preferences and satisfaction levels.

2.2.3 Metapath Discovery Engine:

Design algorithms for metapath discovery that analyze intricate relationships between different product categories. Explore semantic connections and historical patterns to uncover meaningful metapaths, enhancing the understanding of user-product associations.

2.2.4 Dynamic User Models:

Create dynamic user models that adapt to changing preferences and evolving personalities over time. Employ metapath-based insights to continuously refine and update user profiles, ensuring recommendations remain relevant.

2.2.5 Context-Aware Recommendation System:

Incorporate contextual awareness to consider external factors such as seasonal trends, social influences, and emerging preferences. Implement real-time adjustments to recommendations based on contextual information, providing timely and relevant suggestions.

2.2.6 Explainability and Transparency Features:

Integrate features that explain the rationale behind each recommendation, highlighting the influence of personality traits and metapath connections. Provide users with transparency controls, allowing them to customize the level of personal information used for recommendations.

2.2.7 User Feedback Loop:

Establish a continuous feedback loop to collect explicit feedback from users on recommended products. Utilize feedback data to iteratively improve the recommendation algorithms, ensuring a responsive and user-centric system.

2.2.8 Cross-Category Recommendations:

Explore and leverage metapaths to offer serendipitous cross-category recommendations, expanding users' exploration beyond their typical preferences. By integrating these components, our proposed system aims to create an intelligent, adaptable, and transparent recommendation engine that not only understands users' interests but also respects their individual personalities, providing a truly personalized and engaging shopping experience.

2.3 Advantages of proposed system:

The proposed system offers personalized product recommendations by integrating user interest mining and metapath discovery. By analyzing individual preferences, it tailors suggestions, enhancing user satisfaction. Metapath discovery adds depth, identifying intricate relationships in user behaviour for more accurate predictions.

III. MODULES:

3.1.1 Service Provider:

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Train and Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, Predict Product Recommendation From Data Set Details, Find Product Recommendation Prediction Ratio on Data Sets, Download Trained Data Sets, View Product Recommendation Prediction Ratio Results, View All Remote Users.

3.1.2 View And Authorize users:

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

3.1.3 Remote User:

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like Post Product data sets, Predict Product Recommendation, View Your Profile.

IV. OUTPUT SCREENS

User Registration Page:

Fig.4.1. User Registration page

Service Provider Login Page:

Fig.4.2. Service Provider Login Page

User Login Page:

Fig.4.3. User Login Page

Post Product Data Sets:

Fig.4.4. Post Product Data Sets

User Profile Details:

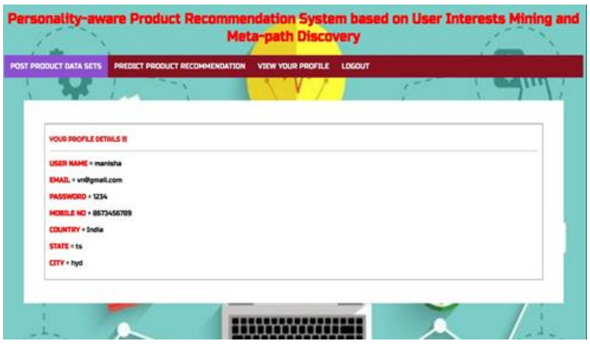

Fig.4.5 User Profile Details

Prediction of Product Recommendation:

Fig.4.6. Prediction of Product Recommendation

Product Recommendation With Prediction:

Fig.4.7. Product Recommendation With Prediction

Trained and Tested Data Sets Results:

Fig.4.8. Trained and Tested Data Sets Results

Details of Remote Users:

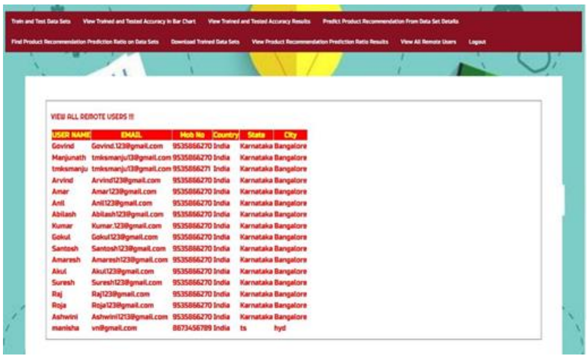
Fig.4.9. Details of Remote Users

View Trained and Accuracy in Bar Graph:

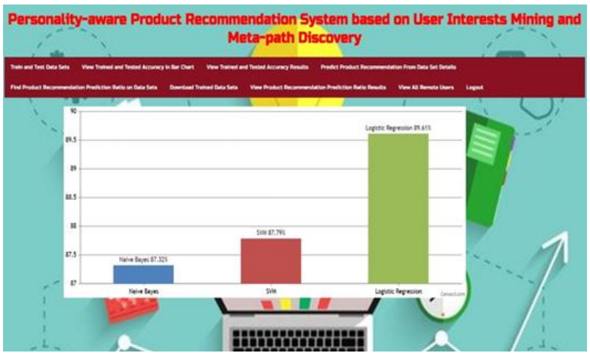

Fig.4.10. View Trained and Accuracy Bar Graph

View Trained and Tested Accuracy Results:

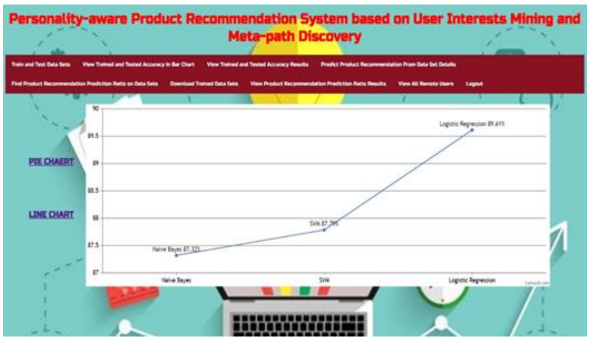

Fig.4.11. View Trained and Tested Accuracy Results

Predict Product Recommendation From Data Set Details:

Fig.4.12. Predict Product Recommendation From Data Set Details

V. CONCLUSION

In this paper, we have proposed a personality-aware product recommendation system based on interest mining and meta path discovery, the system predicts the user's needs and the associated items. Products recommendation is computed by analysing the user's topical interest, and eventually recommend the items associated with the those interests. The proposed system is personality-aware from two aspects, firstly because it incorporates the user's personality traits to predict his topics of interest. Secondly, it matches the user's personality facets with the associated items. Experimental results show that the proposed system outperforms the state-of-art schemes in terms of precision and recall especially in the cold start phase for new items and users.

However, Meta-Interest could be improved in different aspects:

1) In this work, the users' personality traits measurement was conducted through questionnaires. Integrating automatic personality recognition system, that can detect the users' personality traits based on their shared data, into Meta-Interest is one of our future directions.

2) The proposed system uses Big-Five to model the user' personality Extending Meta-Interest to include other personality traits models such as the Myers–Briggs type indicator is a future direction.

3) The proposed system could be further improved by integrating a knowledge graph and infer topic-item association using semantic reasoning.

FUTURE SCOPE

The future scope of a personality-aware product recommendation system, rooted in user interest mining and metapath discovery, is poised for remarkable advancements. As technology evolves, there are several avenues to explore, enhancing the system's capabilities and user experience.

The future of personality-aware product recommendation systems lies in dynamic personality profiling with deep learning, leveraging natural language processing for nuanced interest mining, advancing metapath discovery through graph theory, real-time data integration for up-to-date recommendations, and prioritizing ethical considerations. User feedback loops will ensure continuous improvement, fostering a more personalized and trustworthy experience.

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