Recommender system using personality traits

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Abstract

With the emergence of personality advancements in the field of science and research, recommendation systems are becoming an important and integral part of our daily life. A recommender system is a software application that examines user actions and preferences to provide recommendations for items that align with the user's potential interests. The aim of a recommender system is to offer customized suggestions that enhance the user's experience and satisfaction. Personality-centric recommender systems fall within the realm of recommendation systems that employ information regarding a user's individuality attributes to produce customized suggestions. These recommender systems have the ability to effectively tackle traditional challenges like the cold start problem and sparsity issues. The primary goal of this paper is to systematically conclude the methodologies employed in recommender systems and explore significant applications of personality-aware recommender systems. Personality computing is discussed in which big five model is described in more detail. Deep learning techniques are also included which defines the state of art of recommender system.

Keywords-Recommender system, Personality computing, Personality aware recommender system, Big five model, Cold start problem, Sparsity problem, Collaborative filtering, Content-based filtering, Deep Learning

1. Introduction

It has become very important for businesses to offer products and services that satisfy directly to an individual customer's needs in such a big competitive marketplace. Recommender system is well known term in present time which we are using in our daily life. We always see a section of "people you may know" or "item you may like" on social media apps and e-commerce websites. Big tech companies like Facebook, amazon, google, and Netflix uses recommender system to recommend their services and products. Recommender system suggest users by learning their previous actions and behaviour and predict their current choice for products.

Conventionally, recommender system uses techniques like collaborative filtering and content-based filtering for recommendation. In collaborative filtering, suggestion is given to the users by measuring the same traits among users. In content-based filtering, suggestion is given on the basis of past interaction of users with items they have purchased or liked.

These methods leave some problems unsolved like cold start problem and sparsity problem. The cold start problem arises when a user is unfamiliar with the system, and the system lacks any prior information or data regarding the user's preferences or characteristics. The sparsity problem arises when it becomes challenging to identify similar users because the active users have only rated a minor portion of the items available.

Personality based recommendation system comes to rescue in such problems [1]. It states that personality traits of a person can be used to solve such problems. If the system knows personality traits of users, then it becomes easy to recommend the products when they are new to the system, or the system have less data about the users. Personality traits generally tells every person pattern of thinking, expressing or individual personalities.

Section 1.1 delves into the topic of personality measures, while section 2 covers the fundamental models and methods employed by personality-aware recommender systems. Section 3 explores the deep learning methods used in this field, and section 4 examines the various applications of personality-aware recommender systems. Finally, in section 5, the future prospects of deep learning are discussed, and section 6 of the paper contains the conclusion.

1.1 Personality measures

Identifying the personality type of any person is important task in personality-based recommender system. Any mistake can lead up to inaccurate recommendations. Personality can be measured through two primary methods, namely personality inventories and automatic personality recognition (APR) as outlined in [1].

Personality assessment questionnaires entail individuals providing responses on a five-level Likert scale,such as strongly endorse, endorse, neutral, oppose, and strongly oppose. These questionnaires are available in different lengths to cater to different needs. The main drawback of this practice is that user may find the questionnaire very lengthy and may not fill it. So, short questionnaires [2],[3],[4] are preferred. Multiple personality models, such as the Big Five personality model, PEN model, Myers-Briggs Type Indicator model and 16PF, are employed to evaluate the personality scores of individuals. The Big Five personality design is the most famous criteria for understanding personality held by few psychologists. The theory proposes that human personalities can be categorized into five fundamental factors, often represented by the acronyms CANOE (conscientiousness, agreeableness, neuroticism, openness, and extraversion) or OCEAN (openness, conscientiousness, extraversion, agreeableness, and neuroticism). These five personality traits are considered significant [3]:

1. Openness to experiences(O)-The tendency to appreciate new art, ideas, feelings, and behaviours.

2. Conscientiousness (C)-The tendency of being diligent, punctual, adhering to rules, and displaying a strong work ethic.

3. Extraversion(E)- The tendency to express better, being social and being more dominant.

4. Agreeableness(A)-Tendency to listen everyone, tendency to be a group leader by letting everyone put their views rather than igniting owns views in every mind.

5. Neuroticism(N)-Tendency to express negative emotions of human being such as anger, worry, and sadness, as well as being inter-personally sensitive.

Another drawback of this method is that people may get biased while answering the questions which can lead to inaccurate recommendations.

APR comes to rescue when such problems occur. Automatic personality recognition (APR) can be utilized to process a user's existing data, and subsequently assign a personality score that best corresponds to the individual by gathering information about user from social media. Automated personality recognition (APR) can be classified into three categories: text-based APR, APR using multimedia data, and behaviour-based APR. APR focused on textual data is utilized specifically when the available data comes in the form of text, such as posts or tweets from social media platforms [5]. When the data is in image, voice or video format then Multimedia based APR can be used [6]. And finally, when the data show some behavioural patterns of user like browsing behaviour then behaviour-based APR can be used [7].

This paper discusses the basic models and methods of recommender system and the trending techniques like deep learning which is quite popular research topic these days for recommending product and services.

2. Basic methods and models of personality aware recommender system

In present time, there is lot of content and information on the world wide web which keeps on growing every day. E-services gives a variety of options to users which leads to more complex decision-making. Recommender system comes to rescue us on such problems. Adding personality traits to the system makes it more personalized than ever. In essence, recommender systems employ three primary types of filtering techniques: Content-based filtering, collaborative filtering, and hybrid filtering, which combine elements from both content-based and collaborative filtering techniques.

2.1 Collaborative Filtering

This approach suggests items to the user by considering users who exhibit similar preferences. Collaborative filtering (CF) remains the most extensively utilized technique in recommender systems [8]. The basic research states about CF that, user who have similar taste will share similar items. Hence, a system using this technique totally depends on the information provided by the user about their tastes and which then suggest similar preferences to the given user. This conventional model can be applied in personality aware recommender system. Personality-based collaborative filtering identifies similarities among users by considering their individual personality traits. This type of filtering can be further categorized into two subcategories: personality neighbourhood methods and matrix factorization methods [1]. Different similarity measures like Pearson correlation and cosine similarity etc are used to find the similar users. In personality aware matrix factorization methods, the personality traits of user are combined with its ratings which basically extend the conventional matrix factorization algorithm [1].

In their research, Nalmpantis and Tjortjis [9] developed a recommender system called 50/50 by incorporating the Big Five personality test into pre-existing film recommendation system based on collaborative filtering. The system was evaluated on a widely used movie dataset, and the results revealed that users favoured the 50/50 system over the contemporary method by a margin of 3.6.

2.2Content Based Filtering

In personality aware recommender system, content-based filtering is used in a manner such that system uses user's personality traits and matches with the item with similar personality features. If a user(u1) is interested in action movie M1 and rate(r1) it 5/5 and rates similar categorized movie(M2) 4/5, then 3rd movie(M3) recommended by the system to the user will be according to the compatibility score between the movie and the user's personality and would be of the same category; let say action. Different personality score is given to each item based on content analysis and attribute analysis. In content analysis, a system recognises personality of that item by implementing APR on the textual description or details of that item. As an example, a study [10] employed the product personality scale [11], a method of assessing the personality of products, to evaluate the personality of various items. The system allocates a personality score to each item through attribute analysis, which involves examining characteristics of the item and how they relate to the personality of the user who interacts with it. In short personality matching criteria is applied between the user and the item when system finds something common between them.

2.3Hybrid filtering

Hybrid filtering is a methodology that harnesses the benefits of both content-based filtering and collaborative filtering techniques, synergistically enhancing the performance of recommender systems. Content-based filtering operates on the user's space, while collaborative filtering operates on the item's space. An example of a friend recommender system that utilizes the hybrid filtering approach is presented in [12], where content-based filtering is employed to identify individuals with comparable ratings, and collaborative filtering is used to refine the item space(i.e., potential friends). Another example is a game recommender system that utilizes hybrid filtering, described in [13].

3. Deep learning techniques

In recent times, advanced deep learning models like Recurrent Neural Networks (RNNs), Auto encoders and Convolutional Neural Networks (CNNs)have revolutionized the field of recommendation systems [14]. These models have proven to be effective and powerful tools in improving the accuracy and efficiency of recommendation systems. It has shown tremendous results in personality aware recommendation systems also. Recent advances of deep learning have overcome obstacles of conventional methods and provided better and high quality of recommendations. Deep learning is utilized in two main ways in the field of recommendation systems: (1) to detect and analyse the personality characteristics of users, and (2) to enhance the recommendation process itself.

Majumder et al. [15] proposed a Convolutional Neural Network (CNN) model designed to identify personality traits based on textual data. In their study, Wei et al. [16] developed a Deep Bimodal regression model aimed at detecting personality traits using images and videos.

> ***Multilayer Perceptron (MLP):*** It belongs to the category of feed forward neural networks, characterized by the inclusion of numerous hidden layers positioned between the input and output layers. Unlike other perceptron models, MLPs can use a variety of activation functions and are not necessarily limited to binary classification. MLPs can be visualized as a series of nonlinear transformations stacked on top of each other.

Convolutional Neural Network: The feed-forward neural network described in [17] is unique and convolutional layers and pooling operations are included in it. They are also known as convents. It was first used to recognise digits and alphabets. Now it is used for image processing and object detection. They are used to detect satellite images and anomalies.

TABLE 1: Classification of Personality-aware recommendation techniques

Recommendation method	**References**	**Description**
Personality neighbourhood	[23],[24],[25],[26],[39],[27],[28]	Neighbourhood similarity techniques include K-Nearest Neighbour, Cosine Similarity, Jaccard Similarity, Euclidean Distance, and the widely used Pearson Correlation Coefficient.
Matrix factorization	[29], [30], [31], [32], [33]	Matrix factorization is used to model the relationship between a user's personality traits and their preferences for certain types of items.
Content based Filtering	[34][35], [42], [36]	This approach entails examining the content and attributes of the items within a recommendation system and aligning them with the user's specific preferences.
Hybrid personality filtering	[39],[37], [43]	The integration of content-driven and collaborative filtering allows for a more comprehensive understanding of user preferences and improves the overall recommendation quality.
5. Deep learning	[38], [15],[16], [17], [18], [19], [20], [21], [22]	Utilized for capturing intricate patterns and interdependencies in user-item interactions and personality traits, this approach enables the generation of more precise and personalized recommendations.

Recurrent Neural Network: The RNN is utilized for modelling sequential data, and it has loops and memory units to retain past computations, unlike feed-forward neural networks[17]. To tackle the vanishing gradient problem, LSTM and GRU units, which are neural networks used in AI and deep learning, are commonly applied in practice. Applications such as speech recognition and predictive modelling extensively utilize these techniques.

Auto-encoder: It is a form of neural network that employs the input to reconstruct the output, resulting in a self-tracing or self-referential network architecture. Input is converted by the encoder to the latex dimension from where output extracts data. Image compressed through this gets a no loss compression.

Restricted Boltzmann Machine: It is a neural network architecture comprising two layers, namely a visible layer and a hidden layer. The term "restricted" in the name indicates that there are no direct connections between neurons within the same layer. Restricted Boltzmann Machines (RBMs) are a potent deep learning algorithm that can be employed for diverse tasks including filtering, feature extraction, and categorization. Its ability to learn and extract relevant features from high-dimensional data makes it a popular choice in various fields such as Anomaly Detection and image recognition.

Neural Auto regressive Distribution Estimation: [18][19] is an unsupervised neural network. It can identify the densities and act as an efficient estimator of modelling type data distribution which is tractable.

Adversarial Networks: In [20], two neural networks are generated and are trained to compete with each other in a small framework where one acts as a generator and another as discriminator.

Deep Reinforcement Learning: It is a trial-and-error paradigm that involves several components, including agents, environments, states, actions, and rewards [21]. By combining RL with deep neural networks, it is possible to achieve human-like accuracy. Deep neural networks enable agents to learn from raw data and construct effective representations autonomously, eliminating the necessity for manually designed features or domain-specific rules [22].

4. Application of personality aware recommender systems

Friend recommendation: In [39], a friend recommendation system called Personet was proposed based on users' personality traits. Personality-aware recommendation systems can be useful for suggesting friends on social media who are most compatible with our personality. The Friends recommendation system utilizes data analysis techniques to identify specific user behaviours and personality traits that can be inferred based on diverse metrics, including factors like the quantity of followers and followings, as well as common friends between them. Using this information, the system generates personalized friend suggestions for users to follow, enhancing their social media experience.

Movies recommendation: Personality aware recommendation system can be used to recommend movies to the user on the basis of its personality. If one person like a particular movie, then this movie is recommended to another person having similar personality traits .Golbeck *et al.* [40] found a positive correlation between users' personalities and their preferences in movies.

Music recommendation: Music recommendations can provide insight into a user's personality, as their musical preferences often reflect their individuality. In a study conducted by [41], the research examined the impact of individual characteristics on the accuracy of music recommendation systems. Additionally, [42] presented a hybrid approach to personality-based music recommendations.

Game recommendation: The purpose is to recommend games to the gamers based on their likes, dislikes, and personalities of different users. The burgeoning video game industry stands to gain significantly from the implementation of a recommender system. Such a system would facilitate the introduction of the most appropriate games to the most suitable audiences, thereby generating significant economic benefits for the industry. A personality-aware game recommendation system was proposed in [43] using text mining on social media posts of users to identify their personality types. The system analyses the game content and recommends games on the basis of personality traits of the individuals. This technique aims to provide personalized game recommendations to users, which can enhance their gaming experience.

5. Future aspects of deep learning in personality aware recommender system

The future of deep learning in personality-aware recommendation systems is promising. Some of the discussed aspects include the development of advanced models that can handle high-dimensional and sparse data, the incorporation of additional user data, such as historical behaviour and social network data, and the utilization of transfer learning techniques to generalize models across different personality traits and languages. Moreover, integrating the latest research in psychology and neuroscience can lead to more accurate and comprehensive models of personality, which can help improve personalized feedback and recommendations. Lastly, deep learning models can be applied to predict personality changes over time, which could identify potential interventions to enhance individuals' well-being. These developments may enhance the accuracy and relevance of personalized recommendations and improve our understanding of personality traits.

6. Conclusion

This paper offers a thorough examination of the literature surrounding personality-aware recommender systems, which is supported by numerous research studies. The study illustrates that such systems are exceedingly efficient in tackling the challenges of the cold start and sparsity issues that have persistently troubled conventional recommendation methods. In addition, the paper delves into the latest trends in this field, including deep learning techniques, which offer a valuable glimpse into cutting-edge technologies beyond the conventional methods.

However, one of the major challenges in the development of personality aware recommendation systems is accurately detecting users' personalities while maintaining their privacy. This issue is carefully examined and analysed in this paper, shedding light on the complexities involved in balancing the need for accurate personality detection with the ethical considerations of user privacy. Overall, this paper gives a valuable contribution to the field of recommender systems and highlights the need for further research in this area to address the challenges and opportunities presented by this emerging technology.

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