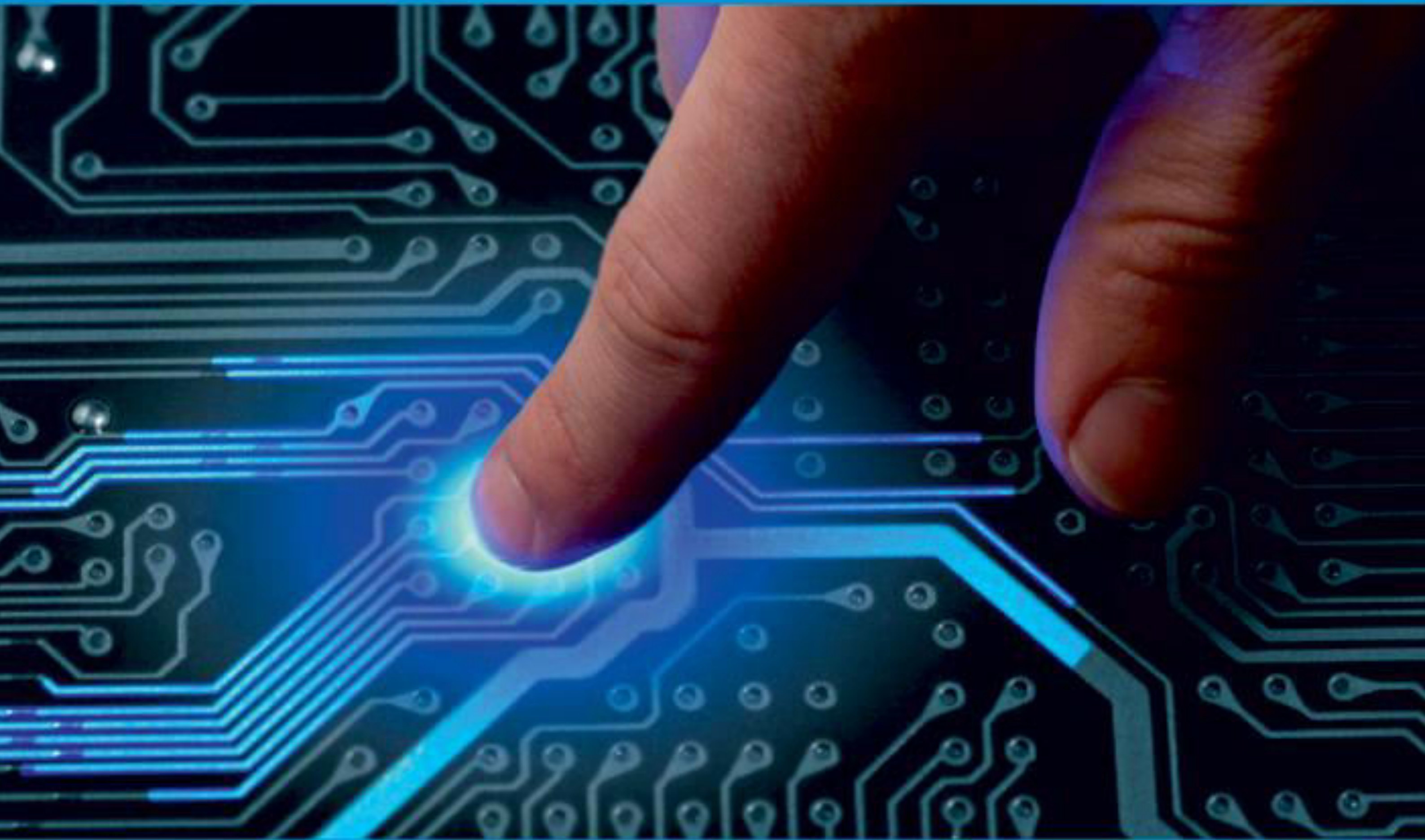
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 5, May 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2023.1205004 |

Recommendation Systems: A Short Review

Nguyen-Tran-Diem Hanh

School of Science and Technology, Tra Vinh University, Tra Vinh City, Vietnam

ABSTRACT: Research in recommendation systems has been gaining popularity since the past few decades. This is particularly popular for dealing with searching over a huge number of ecommerce sites and a large amount of information about different products in the online market. These state-of-the-art systems aim to facilitate Internet users in searching for their relevant information in the environment of overload of information. These good filtering systems help people save a large amount of time for searching relevant information while they are also provided with meaningful and favourite contents. In general, the underlying task of recommendation systems is to provide suggestions about information such as news, books, or consumer products that match with user's preferences given explicitly or implicitly by the users. Many different techniques and algorithms were proposed with the intention to improve performances of recommending systems in the past few years. In this article, some basic types of recommendation systems (RS) are provided such as Content-based RS, Collaborative-based RS and Hybrid-based RS. Besides, this work outlines some current developed social filtering RSs and a common technique used in them, which is Matrix Factorization. Finally, this article presents how to build a recommendation system and evaluate its prediction performance in term of accuracy and coverage factors.

KEYWORDS: Recommendation systems, Collaborative-based RS, Content-based RS, Hybrid-based Recommendation System, Content Filtering, Social Filtering System, Matrix Factorization.

I. INTRODUCTION

In recent years, recommendation systems have been getting a lot of attention from researchers in computer science for different domains. These systems are being widely researched especially in e-commerce websites as given in [1-4]. In general, recommendation systems are software programs providing suggestions of items to a user or a group of users, which significantly contribute to the users in their decision making process of purchasing various products, ranging from news, foods, music and clothes. One of the main criterion for a successful RS is that the recommended items should be matched with user's interests or preferences both explicitly and implicitly. However, with the explosion of information and internet users and the number of items and users are growing in a very fast manner so providing personalized recommendations to each user is an uneasy task. Therefore, there is a need to have more innovative algorithms in filtering methods with more improvements and decisive factors to enhance the accuracy and effectiveness of personalized recommending. In other words, a recommendation system that is able to understand the users is important for generating more relevant suggestions that match with a wide range of users with various preferences.

A typical recommendation system usually comprises of two main components, users' profiles and items' profiles. Users can be a list of different Internet users and items are a set of products that the users may want to purchase or advertisers want to introduce to their prospective customers. Information from users and users' profiles might comprise of information about their demographics, opinions, behaviours in internet browsing or preferences, which depends on different recommending systems. This information can be collected explicitly by asking users to give their opinions about their preferences. The information can be also gathered implicitly through their behaviours of viewing, buying or searching in the websites. The task of representing profiles for items are rather complicated in the aspect of a general model for all RSs since they depend on the products or services to which each RS is targeting. The information for items profiles can be various, ranging from movies, books, tourism sites to music, etc. Hence, what we can say for sure about items representation is that different recommending system models items' profiles differently according to their expectations and intentions.

Once users' profiles and items' profiles are modelled, a recommending technique among three following methods should be determined to develop the system including CbRS, CFRS and Hybrid-RS. In particular, three types of recommendation systems (RSs) are analysed in this article, comprising of content-based RS shorted as CbRS, collaborative filtering based RS shorted as CFRS, and Hybrid RS that is a combination of both a CbRS and a CFRS together. In short, CbRS employs a basic technique of matching between item's attributes and users' preference over the items' attributes. In CFRS, information about user's ratings over the bought or viewed items is used to recommend to new users. In some large systems like movies or books recommending systems as provided in [5, 6], the number of user's profiles and items profiles is huge. Therefore, there is a need for good algorithms for enhancing the recommending performances in terms of accuracy or relevant suggestion, which are analysed and tested carefully. In

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2023.1205004 |

general, majority of techniques in personalized recommendation applied various concepts in computer science and statistics such as Artificial Intelligence, Information Retrieval, Data Mining, Machine Learning, Statistics as mentioned in [4, 7]. This article provides a short review of three current main types of recommendation systems in terms of answering these following questions as below:

- What are the purposes of building personalized recommending systems?
- How to model user's profiles and items' profiles in a recommending system?
- What technique should be used for recommending items that are the best matched with various user's tastes or preferences?
- How to evaluate the performance of a RS?

This article begins with the introduction to deliver readers general information about this work. The related work is presented in Section II before the third section about methods of recommending systems is presented. The final section is the conclusion presented in Section IV.

II. RELATED WORK

As mentioned in the introduction section, recommendation systems can be mainly divided into three main types: content-based recommendation systems, collaborative filtering based recommendation system and hybrid recommendation systems. The first type uses the technique of matching between items' attributes and the items' properties given by the internet users. The second type utilizes previous user's rating on the item when recommending to a new user and the third type is about combination the two other types together.

Content based recommendation systems

A Content-based recommendation system has its roots in data mining, investigating the content of the items being provided to users. In this system, items usually are news or articles with some descriptions about them. The purpose of this kind of system is to recommend personalized contents to new users. Some existing studies of content filtering based recommendations include News Due, News 4U and Your News as given in [8-10]. In particular, News Due provided in [9] is a personalized news recommending system used for providing suggestions news to news readers. This was one of the first recommendation systems that employed the content-based filtering technique. From the technical aspects, this work used TF-IDF parameters and similarity measures to describe news stories for determining the short term recommendation systems. Similarly, another book about recommendation system called LIBRA as provided in [6] presented a content-based recommendation system that used information about books gathered from the Web. This work implemented a Naive Bayes classifier on the information extracted from the web to learn a user profile for producing a ranked list of titles based on training examples. Similar to these studies, News@hand in [1] described item features and user preferences in an ontology to provide personalized news to new users. More specifically, it modelled some specific domain ontologies to define concepts/class using news information related to topics such as education, politics, religion, science, technology, business, and health. When the system reads a news article, it identifies which concepts the article is mentioning. User preferences are identified by an expansion relationship among concepts in the ontology and use the Constrained Spreading Activation (CSA).

Bayesian network was employed in building recommendation systems in which users' profiles were modelled as nodes in a social network of friends as provided in [11]. User's ratings among friends were then used to infer predictions for other new users. That work was said to solve the problems of sparseness and cold start. In terms of performances, the accurate performance of the system provided higher recommending capability than Collaborative Filtering RS systems. Another recommending system for computer science publications called PRS provided in [13] offered a means for authors to submit their manuscripts using the information provided in their abstracts or the whole manuscripts. This work followed the content-based filtering approach where item's profiles were modelled using the abstract of the paper. In terms of technical aspect, chi-square and softmax regression were used to construct the system, which is different to other previous recommending systems. In addition, this work was reported to be innovative to filtering documents about computer science because there was not data set for implementation and testing from any published articles about the domain. Hence, the team working in this work had to collect data and process it from scratch. Another common algorithm used for building recommendation systems include nearest-neighbour methods in which associated with a classifier as a profile as provided in [12]. This method required storing all items and users which have rated. There are some advantages of this innovative method. Relevant recommendation system is the first aspect of the method since recommended items have similar content with user's preferences. In other words, content-based RS can help to generate more objective information in comparison with other methods.

Collaborative recommendation systems

A common method for recommendation systems is collaborative filtering method which was first developed in [14] for sharing information among employees in a company. In general, this method made use of word-of-mouth in advertising, which was thought to provide better suggestions than content-based systems. GroupLens [4] was originally

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2023.1205004 |

designed to recommend Usenet news to Internet users, aiming to provide suggestions for new users using collaborative filtering. Internet users rated their interest over the read news and this information was then used to recommend new users with similar interest. At the beginning stage of recommendation systems, this work was the first system that mentioned about sparse ratings. However, the notion of matrix factorization was not taken into account in that article. Later on, some famous e-commerce websites such as NetFlix.com and Amazon.com as provided in [15] employed this type of filtering technique for recommending entertainment contents such as music, consuming products or movies. In particular, Amazon recommends items for a user viewing a current item on the basis of other users that have viewed the current item. In other words, the system filtered through millions of available items based on preferences or past browsing behaviors of a user. In education domain, this type of social filtering method was also utilized for recommending personalized courses as provided in [16]. The work aimed to recommend suitable learning courses for undergraduate students with similar preferences to the interests of prior students. In general, the main principle of recommendation systems based on social collaboration is using user's interest over the whole products to provide recommendations for new users and ignoring over-detailed information from items themselves. Hence, CFRSs are said to be more flexible to apply to many different domains of information. In addition, it can be said that collaborative filtering method has proven to suggest more relevant items than content based method in terms of recommending some common products such as music and movies as provided in [17]. This result stemmed from using information of items subjectively in recommendation phases through items and users' representation.

Although CFRSs are successful in solving the problem of memory usage and items representation, collaborative filtering systems still posed several problems to researchers in the phase of determining relevant suggestions. One of the obvious problems is the cold-start problem, which happens when new users do not show any preferences over any products, but they need some relevant recommendations. The second problem can be the coverage of user's ratings or user's ratings might be sparse. This is because it is not easy for an internet user to be able to provide ratings over a large number of items under lacks of time, efforts and passions. In addition, distinct preferences from others over product features or characteristics are difficult to recognize. In order to solve the problem of sparseness, matrix factorization is commonly used with the intention to reduce the dimensions of the modelled matrices and hence increase the filtering performance of RSs. Readers might also find some useful methods for solving the cold start problem as provided in [20].

Hybrid Recommendation systems

Content-based approach can be an effective one for solving the "cold-start" problem but typically this approach leads to lower accuracy than collaborative filtering systems. In contrast, there is also an underlying problem with collaborative filtering systems when dealing with sparse ratings, causing sparse matrices. Hence, for the purpose of alleviating these negative sides in the mentioned methods, Hybrid models were proposed with the initial attempt to combine these different kinds of filtering methods to generate better recommendations across the board. In fact, there have currently been a number of significant studies of merging the two methods for the benefit of enhancing quality recommendations. First of all, adaptive web sites in [18] was one of the first studies in combining different methods of filtering systems together with the intention to improve recommendation performance. This work implemented 41 hybrids model in order to find the most suitable models which can handle big datasets. Some recommendation techniques were discussed in this work including content-based, collaborative-based, demographic based filtering and knowledge-based recommendation systems. It also particularly investigated the capability of hybrid models in recommending food to customers at a restaurant called Entrees.

One of the interesting studies is a hybrid approach as in [3] which investigated how to incorporate both content-based filtering and collaborative-based filtering methods together to provide recommendations of movies and shopping. It followed the probabilistic approach that investigate the joint distribution of a set of binary variables through their pairwise interaction to implement the recommendation system. The probabilistic model was used to provide user's preferences over items using their previous actions. This new model generated a higher accuracy than other item-item based collaborative filtering systems. This work was said to suggest better recommendations in terms of cold-start and not cold-start problems.

A similar approach in recommending items to users using hybrid filtering methods was studied in [19]. It employed both techniques in data mining and machine learning in filtering latent information from a large movies data source to improve recommending performance in terms of accuracy and coverage. In particular, a combination between Naive Bayes classifier and collaborative filtering was used in recommending movies, which are the most suitable to users who would like more information about movies. It was said to improve the accuracy and coverage of recommendation systems. Another method for collaborative filtering is exploiting both semantic meanings and dimensional reduction for recommendation as described in [20]. To be more specific, an ontology comprising concepts and relationships among the concepts was proposed for modelling item profiles to solve the recommending problem.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2023.1205004 |

III. METHODS

Although there are currently many different recommendation systems for various domains of information, there is not a general method that can be applied for all. However, it can be said that there is a relatively suitable set of steps for majority of recommendation systems. In particular, in order to build a recommending system, three main steps including processing data, modelling item representation and building a user preference model can be followed as below:

A. Data Collection and Reprocessing

Creating an ontology from raw contents is one effective method of processing data in recommendation systems. News@hand [1] is one of the first studies that uses predefined possible concepts relating to the articles in some common social issues. More specifically, in order to provide some seed concepts for the ontology, this work employs WordNet dictionary for frequent nouns and Wikipedia for proper names. When the system reads RSS files from famous websites such as BBC, CNN, The New York Time, and the Washington Post, they identify the concepts of each article for forming the ontology. Working that way, a book recommendation system as mentioned in [20] also builds an ontology about concepts used as features for providing books recommendations. An interesting aspect of that work is that data was collected from scratch, not from any predefined datasets.

Other methods of getting user's information are explicit and implicit feedback from users. GroupsLen in [4] collects user's preferences by asking the viewers to rate the news they have read. This explicit method can provide reliable information for the later filtering process. Besides these articles in Usenet News are not only simple news, these articles also contain some general information about physical products and their physical properties. Usenet news provided a high number of items per day while one typical user just could read a certain number of articles a day. This leads to low numbers of ratings over items compared to the total items used for recommending. Similarly, the work provided in [3] also followed similar method of filtering relevant information given by GroupsLen, which used collected user's information through their explicit ratings over recommended products.

Exploiting information of items themselves and combining with explicit feedback from users is another way in this data collection and processing phase. LIBRA system in [6] uses content-based filtering approach over book information extracted from web pages at Amazon.com in the book items for recommendations. In particular, specific information about books including publishers, dates, ISBN, prices are used as user's preferences. User's preferences are recorded by having users rate on the books that they have read in 10 scale. This work collected a large number of book titles, about 3061 titles of books, with abstracts or customer's reviews. In [13], an automatic web crawler is constructed to collect abstracts from 28 journals and 38 conferences for data. The data then was processed in some steps including tokenization, stemming and removing stop words.

There are also other ways of gathering raw item data from the Internet environment. As provided in [3], the data is collected from purchasing records from customers over a period of time. In the case of recommending apparel products, the authors use the method of reading many retail websites. As given in [3], after gathering product descriptions, they apply Naive Bayesian Classification to classify texts into 8 features. In other words, each apparel profile should be modelled with 8 features.

B. Item representation

Item profiles of a recommendation system can be products or users. The product profiles are usually the object features, which may be recommended to the users. The user profiles are collected information from the internet users implicitly or explicitly. After these data used for recommendation systems is collected, it should be organized in a structure that can be used for the later recommending phase. Currently, there are various possible approaches to present the knowledge of users and products including creating an ontology as in [1, 20] or using relational database system and means-end chain model. In general, some general information about how to store products and user profiles is listed as below.

One of the possible methods of representing item profiles is building a knowledge base or an ontology. A knowledge base can be used to present information about users and products. Product descriptions from retail websites can be used to build a knowledge base of products. These distinct features can be used in the later recommendation phase. The study that investigated the relationships between concepts of items was provided in [20].

Similar to ontology, Means End Chain Model is appropriate to recommend items cross product categories. When this source of knowledge is used for item representations, it is designed in the form of a diagram that shows sets of product profiles, products attributes and the benefits that these products might bring to users when using them. In particular, a product profile can be described in terms of two parts, a Means and an End. The Means is used to represent product features and the End is used to address the utilities of that product. In order to generate a good Means-End-Chain diagram for a certain product, there is a need to have an expert in the corresponding domain of information.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2023.1205004 |

Recommendation systems that apply collaborative-based filtering methods often use matrices to represent the user's ratings on the items. For instances, a utility matrix $R(U_m, I_n)$ can be used to describe the level of user's interest U_m over the item I_n. This representation is said to be beneficial for large recommending systems where similar preferences are common among users. However, the latent problem of this representation method is that this leads to the high numbers of missing ratings or sparse matrices. This is because users only rate on a limited number of items while there is a large number of items and users in the recommended items list.

C. Recommendation Phase

This phase is one of the most important ones in any recommendation systems as it contributes significantly to determine the success of the filtering systems. Because there has been no general method for all recommendation systems, different methods were designed for handling with a certain type of recommended items. In general, majority of recommending systems use investigation of the relationships between item profiles and preferences of previous users over the items. More specifically, these recommendation systems conduct a matching between a new user's profile and the list of items in the recommending phase, which might cost more in terms of memory capacity and time spent for processing a large number of users and items. Hence, many different methods were introduced to solve the mentioned problem and enhance the performance of the recommending tasks. In this section, a
brief summary of some common methods used for enhancing filtering performance in content-based, collaborative-based and hybrid-based approaches have been provided. This section provides details of a very popular method used in collaborative filtering, which is a Matrix Factorization method. The method has been used widely in recommending movies, music, student performances or books as provided in [2, 5, 21].

Firstly, News@hand, which follows a content-based approach in recommending news as given in [1], utilized an ontology to represent item features and user preferences. An item profile vector is presented as $I_n = (I_{n1}, I_{n2}, \dots, I_{nk})$ where $I_{nk} \subset [0,1]$ describes the relevance of the item I_n concepts in the item content. Similarly, user preference profiles and item profiles are described in the form of a vector space.

$U_m = (U_{m1}, U_{m2}, \dots, U_{mk})$ where $U_{mk} \subset [-1,1]$ manifest the level of interest of user U_m over the concept k. Matching between item information and a user's profile is calculated using the modelled vectors. $Pref = 0$ means that the user is not interested in the prospective item. On the other hand, $Pref = 1$ means that the item can be suggested to that user.

Secondly, for recommending systems using implicit feedback from users, the users profile is identified based on the recorded items, which the users have read or viewed. These users' profiles will be updated continually and the probability of new suggested item over the list of previously seen items will be calculated according to the changes. Item profile of this type of recommendation systems is generated using items' information in its knowledge base. The matching phase for using implicit feedback simply compares between user profile and the item profile in the knowledge base. Some existing methods for this type of recommending systems are presented in [18].

D. Matrix Factorization for collaborative filtering systems

In collaborative filtering systems, Matrix Factorization technique has become popular in the last few years since it provides the ability to generate higher accurate results than other conventional methods. In addition, this method is said to be able to provide flexibility in some cases as given in [2, 5, 21]. In particular, the method was claimed to be suitable for filtering systems that use explicit feedback for recommending items to new experienced users. However, there is a problem with the explicit feedback since users only provide ratings for the items they preferred causing the problem of sparse matrices. More specifically, users are not often providing ratings for all items in the item list but a small number of items provided in the products collection. As a result, the number of unrated items given by the user is large, which leads to a large number of entries assigned as 0 in the $U_m \times I_n$ matrix. This situation is even worse when users provide much less ratings in the item collections, resulting in sparseness of matrices. Therefore, it is important to design a method that can help to reduce the number of calculations over a large number of entries in the utility matrix. Indeed, this can be solved by using the method of dimension reduction on the $U_m \times I_n$ matrix as provided in [2, 5, 21].

Matrix Factorization (MF) is a powerful technique to find a hidden structure behind data. MF was found to be an accurate method to reduce the problem from high levels of sparsity in RS databases. Specifically, this approach is particularly beneficial for systems suffered with missing values.

According to [2], recommendation models based Matrix Factorization use latent factor space of dimensional f to model users U_m and items I_n. Each item i is associated with a vector $q_i \in R^f$ and each user is associated with a vector $p_u \in R^f$. The dot product between vector of users and vector of item noted as $q_i^T p_u$ present the interaction between user and the item. This is also the user $u^0 s$ rating over the item i, denoted as r_{ui}. The rating prediction of user u over item i is calculated as below:

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2023.1205004 |

$$\hat{r}_{ui} = q_i^T p_u$$

The main job of this approach in prediction is to calculate these vectors q_i, $p_u \in R^f$ for the rating prediction of user p_u over the item q_i. This approach has been used and developed in some RSs as provided in [2, 20].

E. Methods to evaluate a recommendation system

Like other information retrieval systems, a recommendation system also has to search within its data storage for relevant content that satisfies user's needs in information. Hence, the system can be evaluated based on its quality and computational efficiency. Quality evaluation is used to assess the ability of an automatic RS to suggest relevant data to user's preferences. Obviously, the purpose of the evaluation is that both sellers and prospective customers benefit from high quality suggestions. For the most part, sellers have a reliable tool to target their prospective customers through the system. Likewise, prospective purchasers have a reliable channel to be informed about the products information, which might satisfy their desires. Evaluation on computational measure aims to assess the ability of a recommendation system to handle a large number of item profiles. In general, some popular methods of assessing a RS include Mean Absolute Error (MAE), Root Means Square Errors (RMSE), Precision and Recall as provided below.

1) Mean Absolute Error (MAE): The Mean Absolute Error (MAE) measures the differences as absolute value between the prediction of the algorithm and the real rating would be given by the user. It is computed using the formula:

$$MAE = \frac{\sum_i^k (p_i - r_i)}{k}$$

Where:

p_i is the prediction of a user over i^{th} item

r_i is the actual rating of i^{th} item given by the user

k is the number of items that the user has rated

MAE was employed in [19, 20, 22] to assess the effectiveness of their designed recommending systems with the intention to select the best model with the highest recommending performance.

2) Root Means Square Errors (RMSE): This method of assessment is appropriate to the recommending systems with a high number of missing values. Some collaborative filtering systems make use of this method to evaluate performances among different methods as provided in [2, 4]. The reason is that this measurement can measure the different between predicted value and the observed value for an item. In collaborative filtering system, it is obvious that the major task is to deal with missing values and to design appropriate algorithms to predict these missing values. Hence, using RMSE is specifically suitable to the collaborative-filtering approach. Several recommending filtering systems used this method to measure performances of them as given in [12, 23].

$$RMSE = \sqrt{\frac{\sum_i^k (p_i - r_i)^2}{k}}$$

Where:

p_i is the prediction rating for i^{th} item

r_i is the actual rating of the i^{th} item

k is the total number of rating predictions

3) Precision and Recall: This accuracy metric can be used to measure how good a recommendation system is in terms of accuracy. In particular, it aims to measure the ratio of relevant recommending retrieved using the system. Precision is defined as the ratio of relevant items to recommended items. Recall parameter is defined as the proportion of relevant items that have been retrieved to the total number of relevant items. Precision and Recall measures can be computed using the following formula:

$$Precision = \frac{X \cap Y}{Y} \quad Recall = \frac{X \cap Y}{X}$$

Where: X is relevant items retrieved Y is the relevant items in the system.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2023.1205004 |

This measurement index was employed successfully in some existing studies as given in these following studies [3, 6, 20, 23].

IV. CONCLUSION

This paper has addressed the importance of recommendation systems in this current information age. In particular, with the explosion of e-commerce websites and a growing number of Internet users shopping online, this area of research is getting more attention and investment from research institutions and large companies worldwide. This work has reviewed popular recommendation systems including content-based, collaborative-based, and hybrid-based approaches. General aspects of a recommending system are analysed for building the system. These include how to model users' profiles, items' profiles and how to provide the most relevant suggestions to new users. In addition, a major method of implementing a collaborative-based recommendation system has also summarized in this article, which is matrix factorization. In addition, this work provided several common factors for performance assessment of a recommendation system in terms of accuracy and relevance. For future development, this work can be developed by providing more in-depth information about content-based filtering and hybrid-based filtering. Finally, the methods for filtering relevant items based on user's interest and methods of the technique assessment should be given in details for the future systematic review.

CONFLICT OF INTEREST STATEMENT

We declare that we have no conflict of interest

REFERENCES

[1] I. Cantador, A. Bellog´ın, and P. Castells, "News@ hand: A semantic web approach to recommending news," in *Adaptive Hypermedia and Adaptive Web-Based Systems: 5th International Conference, AH 2008, Hannover, Germany, July 29-August 1, 2008. Proceedings 5*. Springer, 2008, pp. 279–283.

[2] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, vol. 42, no. 8, pp. 30–37, 2009.

[3] A. Gunawardana and C. Meek, "A unified approach to building hybrid recommender systems," in *Proceedings of the third ACM conference on Recommender systems*, 2009, pp. 117–124.

[4] J. A. Konstan, B. N. Miller, D. Maltz, J. L. Herlocker, L. R. Gordon, and J. Riedl, "Grouplens: Applying collaborative filtering to usenet news," *Communications of the ACM*, vol. 40, no. 3, pp. 77–87, 1997.

[5] Y. Koren, "Factorization meets the neighborhood: a multifaceted collaborative filtering model," in *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, 2008, pp. 426– 434.

[6] R. J. Mooney and L. Roy, "Content-based book recommending using learning for text categorization," in *Proceedings of the fifth ACM conference on Digital libraries*, 2000, pp. 195–204.

[7] A. Calero Valdez, M. Ziefle, K. Verbert, A. Felfernig, and A. Holzinger, "Recommender systems for health informatics: state-of-the-art and future perspectives," *Machine Learning for Health Informatics: State-of-the-Art and Future Challenges*, pp. 391–414, 2016.

[8] J.-w. Ahn, P. Brusilovsky, J. Grady, D. He, and S. Y. Syn, "Open user profiles for adaptive news systems: help or harm?" in *Proceedings of the 16th international conference on World Wide Web*, 2007, pp. 11–20.

[9] G. J. Jones, D. J. Quested, and K. E. Thomson, "Personalised delivery of news articles from multiple sources," in *Research and Advanced Technology for Digital Libraries: 4th European Conference, ECDL 2000 Lisbon, Portugal, September 18–20, 2000 Proceedings 4*. Springer, 2000, pp. 340–343.

[10] D. Billsus and M. J. Pazzani, "A personal news agent that talks, learns and explains," in *Proceedings of the third annual conference on Autonomous Agents*, 1999, pp. 268–275.

[11] X. Yang, Y. Guo, and Y. Liu, "Bayesian-inference-based recommendation in online social networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, no. 4, pp. 642–651, 2012.

[12] R. Ahuja, A. Solanki, and A. Nayyar, "Movie recommender system using k-means clustering and k-nearest neighbor," in *2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*. IEEE, 2019, pp. 263–268.

[13] D. Wang, Y. Liang, D. Xu, X. Feng, and R. Guan, "A content-based recommender system for computer science publications," *Knowledge-Based Systems*, vol. 157, pp. 1–9, 2018.

[14] T. W. Malone, K. R. Grant, F. A. Turbak, S. A. Brobst, and M. D. Cohen, "Intelligent information-sharing systems," *Communications of the ACM*, vol. 30, no. 5, pp. 390–402, 1987.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2023.1205004 |

[15] G. Linden, B. Smith, and J. York, "Amazon. com recommendations: Item-to-item collaborative filtering," *IEEE Internet computing*, vol. 7, no. 1, pp. 76–80, 2003.

[16] M. Diem, "Personalized course recommendation in formal learning based on logistic regression," *International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE)*, vol. 4, no. 10, pp. 521–527, 2015.

[17] P. Resnick and H. R. Varian, "Recommender systems," *Communications of the ACM*, vol. 40, no. 3, pp. 56–58, 1997.

[18] R. Burke, "Hybrid web recommender systems," *The adaptive web: methods and strategies of web personalization*, pp. 377–408, 2007.

[19] M. Ghazanfar and A. Prugel-Bennett, "An improved switching hybrid recommender system using naive bayes classifier and collaborative filtering," 2010.

[20] M. Nilashi, O. Ibrahim, and K. Bagherifard, "A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques," *Expert Systems with Applications*, vol. 92, pp. 507–520, 2018.

[21] Q. Yuan, G. Cong, K. Zhao, Z. Ma, and A. Sun, "Who, where, when, and what: A nonparametric bayesian approach to context-aware recommendation and search for twitter users," *ACM Transactions on Information Systems (TOIS)*, vol. 33, no. 1, pp. 1–33, 2015.

[22] L. Baltrunas, B. Ludwig, and F. Ricci, "Matrix factorization techniques for context aware recommendation," in *Proceedings of the fifth ACM conference on Recommender systems*, 2011, pp. 301–304.

[23] P. Cremonesi, Y. Koren, and R. Turrin, "Performance of recommender algorithms on top-n recommendation tasks," in *Proceedings of the fourth ACM conference on Recommender systems*, 2010, pp. 39–46.

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

Scan to save the contact details