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Recommendation Systems: A Review

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Recommendation systems have become one of the most widespread types of systems today, as they have become a necessity and a need. Recommendation systems can be defined as methods for presenting or marketing electronic products (in various forms) to users, with the selection of products based on the user's actual needs. This is achieved through the use of specific algorithms and methods to gauge the user's interest in the suggested products. Recently, the applications of recommendation systems have expanded beyond a single field or aspect, extending into many areas of life and science. Many methods have been developed and improved for building recommendation systems from naive to advanced ones. This study aims to provide a comprehensive overview of recommendation systems: definitions, objectives, and types, including the advantages and disadvantages of each type.

Keywords: Recommender system, Machine learning, Content-based filtering, Collaborative filtering

1. INTRODUCTION

In recent years, the need for recommendation systems has emerged due to the increased use of the Internet and the vast amount of data available, making it difficult for users to find everything they are searching for. Recommendation systems are defined as computational tools that suggest products to users that might be useful or interesting without the need for direct search. In other words, recommendation systems can be considered as filters that job is to filter data to suggest the most relevant once to the user. Recommendation systems have become an essential feature with benefits for both websites and users; Amazon, YouTube, Facebook, and Netflix are all having their own recommendation system. Today, recommendation system plays a major role in our daily web browsing, so we are all, in one way or another, use or benefit from recommendation systems. For instance, when a user on YouTube watches a video titled "Introduction to Python," other videos similar in content to the first video will be suggested. This not only benefits YouTube as a tool for promoting videos but also provides value to the users by offering content that automatically meets their needs. Similarly, when a user on online store, such as Amazon, purchases a specific product, Amazon will suggest other books with similar content or titles. In general, online suggestions, such as a book to read, a video to watch, a place to travel, or even a food to eat, are results of recommendation systems that have become an integrated service for many websites.

In addition to what has been mentioned about recommendation systems, recommendations are not limited to suggest similar products but also related products, such as device accessories if there is any. For instance, when a user buys a laptop, suggestions may include headphones, a keyboard, or a mouse.

Recommendation systems are built using various methods and algorithms, each with its own advantages and disadvantages. These methods are employed based on specific needs and the data available, as we will explore further. Generally speaking, the past user behavior plays the major role to build recommendation systems. In addition, other factors, such as product popularity, many also be considered. Figure 1 shows the overall and general types of recommendation systems.

Recommendation systems field has been evolving very fast, and a lot of research has done into this field. Early approaches of building recommendation systems may generate their suggestions using simple similarity methods, such as cosine similarity. However, because of limitations that have faced the first-generation methods, new advanced machine learning methods have been introduced to overcome these limitations and to enhance recommendation accuracy. In the following sections, each type will be discussed in detail, including its definition, principles, advantages and disadvantages, along with a number of papers that have addressed each type.

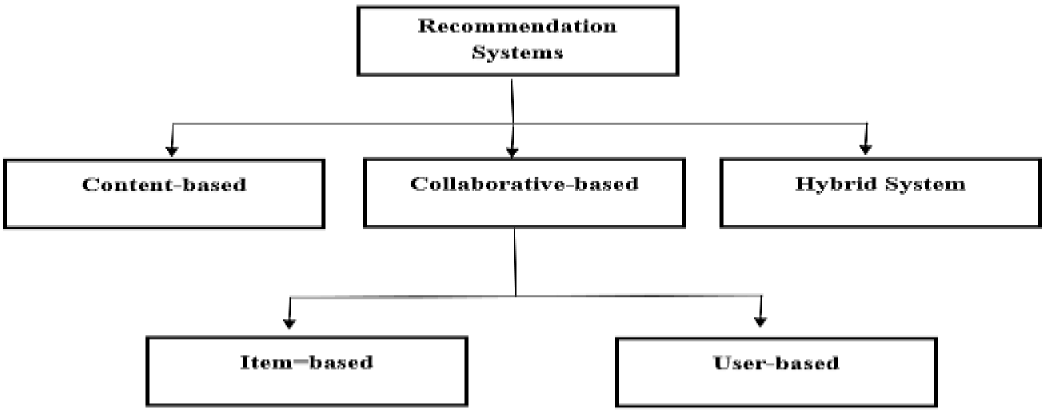

Figure 1. Recommendation Systems Types

2. CONTENT-BASED RECOMMENDATION SYSTEMS

A content-based recommendation system (CBRS) is a type of recommendation system that suggests items to users based on user preferences and the characteristics of the content itself. Unlike other systems that rely on user interactions with other users, this method focuses on analyzing the features of content that users have shown interest in and making recommendations based on these features. For instance, if a YouTube user has searched for video of "Data Science in Python" then the content-based recommendation model will recognize the user preference and may suggest other videos that related to Data Science as well as additional Python-related video.

Practically, user-profile, item-content, and model-building are the main three parts to build a content-based recommendation engine. Where in user-profile matrix, each row represents a user, and each column represents a feature; while in Item- content matrix, each row represents an item, and each column represents a feature. These parts are shown in Figure 2.

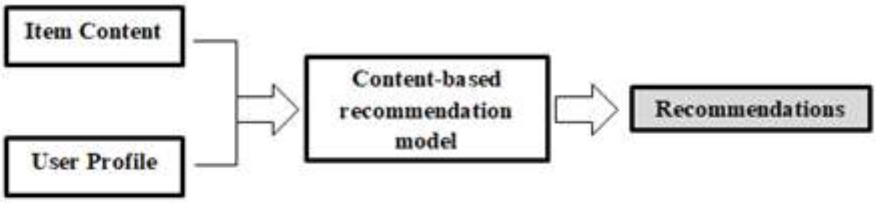

Figure 2. CBRS Parts

2.1. Approach of CBRS

To develop a content-based recommendation system, different steps and algorithms should be implemented. Firstly, algorithms that transform text into numerical or vector representations, such as Bag-of-words, one-hot encoding, and TF-IDF (Term Frequency-Inverse Document Frequency), need to be employed. Also, word embedding's techniques may be used to represent text as features with the advantage of capturing the context of words. Methods such as Word2Vec, GloVe, and FastText can be used to represent text as dense vectors to obtain more accurate results of recommendation systems. The topic of converting text into numerical data has been addressed in various independent studies and research papers, such as [6][4][8].

After the numerical representation of the data is created, similarity algorithms, such as cosine similarity are used to find similarities. Jaccard similarity and Euclidean distance are other similarity algorithm that may be used instead of cosine similarity to compute similarities. Similarity algorithms have been studied in various papers such as [1][13][18][24][29][41].

2.2 Advantages and Disadvantages of CBRS

User-independence can be considered as the main advantage of content-based recommendation system. Meaning that all the suggestions will be introduced based on the past user preferences, and no neighbor is considered. As a result, all the new suggested items are fit to the user interest, unlike other methods. Moreover, unlike other recommendation types, using content-based recommendation systems, new users can get suggestions without problems, specifically referring to the cold-start problem that will be discussed later. This makes it suitable for electronic platforms that lack user data.

However, neglecting to consider nearby users or items may also lead to disadvantages which is over-specialization and limitations in the suggestion list, meaning that users will only get suggestions related to domain that they are already known.

2.3 Research Papers on CBRS

Content-based recommendation system type was discussed in detail in various survey papers, such as [31][27][19]. Moreover, this recommendation type has been used to address different recommended problems. For instance, in [45], a content-based recommendation was introduced for computer science publications to suggest suitable journals or conferences based on the abstract of the research paper. Also, in [28], a content-based type was adopted to enhance tagging recommendation on social media platform. Authors in [42] introduced a content-based recommendation system by implementing a multi-attribute method to calculate similarities.

3. COLLABORATIVE- FILTERING RECOMMENDATION SYSTEMS

Another very popular type of recommendation systems is Collaborative-Based filtering (CFRS). The main concept behind this kind is to use the power of sociality to make suggestions. More clearly, the neighbors of a particular user, play the main role to find recommendation items. Therefore, to implement a collaborative-based recommendation system and make suggestions for a user (named User A, for example), the similar users of User A must first be identified. Finding similar users means to recognize users' behavior and how they interact with items. Therefore, the main step of developing this type is to build a matrix that represents how a particular user interacts with a particular item. The main assumption behind this type is that: users who have shown same interest in the past, they will probably show the same interest in the future.

3.1 Approach of CFRS

Collaborative-based filtering can be classified into two sub-categories, named: item-based filtering and user-based filtering. In the first type, similarities between items are calculated. The goal is to find how, for instance, Item A is similar to Item B based on how they were rated by users. In contrast, in the second type, similarities between users are measured. The goal is to find how for example, User A is similar to User B based on the past behavior (purchased, rated, etc...). Collaborative-based recommendation systems can be implemented even using a memory-based approach or model-based approach. In memory-based approaches similarities are calculated directly using similarity algorithms such as cosine similarity and Jaccard similarity. This approach has been used in many research papers, such as [26][38]. In model-based approaches machine learning algorithms are used to discover the hidden pattern with data and try to predict the unrated items. K-Means machine learning algorithm was used in [3] to build a collaborative filtering recommendation system. While KNN algorithm was used in [11][22] to develop a movie recommender system. Beside the direct use of machine learning algorithm, matrix factorization is one of the most common approaches to build a model-based recommendation system. Matrix factorization, works by dividing the main ratings matrix that has all users and items into two smaller matrices (user matrix and item matrix) in a way that the original matrix can be approximated by multiplying the two small matrices. In user-matrix, each user is represented as vector that captures the user's preferences. While in item-matrix, each item is represented as vector that captures the characteristics of the item. After generating the above two matrices, the next step is to build a model on available rating data, so unavailable ratings can be predicted. More clearly, if there was a user X who has not rated item A, the rated value can be predicted by multiplying the vector of user X with the vector of item A. A model can be built using different machine learning algorithms such as Singular Value Decomposition (SVD) and K-Nearest Neighbors (KNN). Matrix factorization was introduced in many papers, such as [22][38].

3.2 Advantages and Disadvantages of CFRS

Beside the accuracy and simplicity of implementation, one of the main advantages of collaborative-based recommendation systems type is the ability of generating a wide range of recommendations. Moreover, this kind is appropriate to implement when information about items is not available, since it does not depend on content's attributes. However, this type also has its limitations and problems. The cold-start problem is the main issue of collaborative-based recommendation systems. This problem appears with new users where there is no data available, so find and calculate the neighbors is impossible. Cold start problems have been addressed in many papers such as [34][17][7][32][14][36][10][12][23][33][43][44][46] and different solutions have been introduced to overcome this problem. In addition, heavy computations is another problem that need to be considered while developing a collaborative-based recommendation system. For clarity, supposing that a dataset has 1,000,000 users, and 5,000 items, so to find similarities of one user, comparisons with the other 999,999 users need to be calculated. Moreover, bias to popularity is another issue that may appear causing that lesser-known products, that might be valuable, will not be discovered.

3.3 Research Papers of CFRS

A collaborative filtering recommendation system was introduced in many research papers, some of which will be mentioned below. In [35] a multi-level collaborative filtering recommendation system was introduced to improve the suggestions. Moreover, Item-based method was adopted in [40] to introduce a collaborative filtering engine. Also, a research paper recommender system was introduced in [16] based on collaborative filtering method. In addition, authors in [33] were discussed this type of recommendation in detail.

4. HYBRID SYSTEMS

Different and various types of recommendation systems can be combined together to introduce a hybrid recommendation system that may overcome limitations and short-comes that a particular recommendation system type may have. To build a hybrid recommendation system, some approaches may be applied, such as Weighted method, Mixed method, and Cascade method. In Weighted method use various recommendation approach in parallel, and the results will be combined with specific weights to make the final recommendations. While in Mixed method the suggestions are generated separately then they are mixed before sending to the user. In contrast, using Cascade method, recommendation methods are implemented sequentially. Meaning that the outcomes of the first method may be refined by the second method to introduce the final recommendations. The hybrid approach of building a recommendation system was discussed in many papers, some of which will be mentioned below. For instance, authors in [39] discussed the hybrid approach to introduce a movie recommendation system. A new approach to build a movie hybrid recommendation system was introduced in [5]. A hybrid recommendation system was also presented in [15][25] using collaborative filtering and content-based filtering. A hybrid-based approach was also adopted in [9] to build a movie recommendation system. There are other types of recommendation systems that are less common and used on a smaller scale, such as Popularity-Based Recommendation System that made suggestions based on the most popular items among all users. The recommendations are typically based on factors such as highest number of views, ratings, or purchases that an item has received [21]. There is also a Location-Aware Recommendation System type, which provides suggestions based on the user's geographic location [31]. In contrast, Context-Aware Recommendation System, suggests items based on various contextual factors, including the user's current situation, environment, or activity [2].

5. CONCLUSION

Without doubt, recommendation systems have become part of our daily online browsing. Online stores, social media platforms, and other websites have their own build-in recommender system. In this work, author tried to introduce a comprehensive study of recommendation system types, including their concepts, advantage and disadvantage. Also, many related papers that address recommendation systems were mentioned in this study. The aim was to provide other researchers, who interested in this field, with information that may need to begin their own research in this important area.

REFERENCES

[1] Abdul, Wajeed & Adilakshmi, T.. (2011). Different similarity measures for text classification using KNN. 2011 2nd International Conference on Computer and Communication Technology, ICCCT-2011. 41-45. 10.1109/ICCCT.2011.6075188.

[2] Adomavicius, Gediminas & Mobasher, Bamshad & Ricci, Francesco & Tuzhilin, Alexander. (2011). Context-Aware Recommender Systems. AI Magazine. 32. 67-80. 10.1609/aimag.v32i3.2364.

[3] Al Bakri, Nadia & Hashem, Soukaena. (2019). Collaborative Filtering Recommendation Model Based on k-means Clustering. Al-Nahrain Journal of Science. 22. 74-79. 10.22401/ANJS.22.1.10.

[4] Al-Ansari, Khaled. (2020). Survey on Word Embedding Techniques in Natural Language Processing.

[5] Amini, Monireh & Nasiri, Mahdi & Afzali, Mehdi. (2014). Proposing a New Hybrid Approach in Movie Recommender System. International Journal of Computer Science and Information Security. 12.

[6] Andrabi, Syed & Wahid, Abdul. (2022). A Comparative Study of Word Embedding Techniques in Natural Language Processing. 10.1007/978-981-16-9573-5_50.

[7] Angadi, Anupama & Gorripati, Satya & Varma, P.. (2018). Temporal Community-Based Collaborative Filtering to Relieve from Cold-Start and Sparsity Problems. International Journal of Intelligent Systems and Applications. 10. 53-62. 10.5815/ijisa.2018.10.06.

[8] Azarijafari, Mohammad. (2021). A Survey on Word Embedding Techniques in Text Processing.

[9] Basak, Sayani & Chowdhury, Sneha & Goswami, Soham & Gayen, Tousik & Pandey, Shatakshi & Sarkar, Rupanwita. (2023). Movie Recommendation Using Hybrid-Based Approach. American Journal of Electronics & Communication. 4. 12-18. 10.15864/ajec.4203.

[10] Berisha, Fjolla & Bytyçi, Eliot. (2023). Addressing cold start in recommender systems with neural networks: a literature survey. International Journal of Computers and Applications. 45. 1-12. 10.1080/1206212X.2023.2237766.

[11] Cui, Bei-Bei. (2017). Design and Implementation of Movie Recommendation System Based on Knn Collaborative Filtering Algorithm. ITM Web of Conferences. 12. 04008. 10.1051/itmconf/20171204008.

[12] Gope, Jyotirmoy & Jain, Sanjay. (2017). A survey on solving cold start problem in recommender systems. 133-138. 10.1109/CCAA.2017.8229786.

[13] Gomaa, Wael & Fahmy, Aly. (2013). A Survey of Text Similarity Approaches. International Journal of Computer Applications. 68. 10.5120/11638-7118.

[14] Gorripati, S.K., & Vatsavayi, V.K. (2017). Community-Based Collaborative Filtering to Alleviate the Cold-Start and Sparsity Problems.

[15] Gunasekar, Geetha & Iqubal, Safa & Chelladurai, Fancy & Saranya, D. (2018). A Hybrid Approach using Collaborative Filtering and Content-based Filtering for Recommender System. Journal of Physics: Conference Series. 1000. 012101. 10.1088/1742-6596/1000/1/012101

[16] Haruna, Khalid & Ismail, Maizatul Akmar & Damiasih, Damiasih & Sutopo, Joko & Herawan, Tutut. (2017). A collaborative approach for research paper recommender system. PLOS ONE. 12. e0184516. 10.1371/journal.pone.0184516.

[17] Hasan, Mahamudul & Roy, Falguni. (2019). An Item–Item Collaborative Filtering Recommender System Using Trust and Genre to Address the Cold-Start Problem. Big Data and Cognitive Computing. 3. 39. 10.3390/bdcc3030039.

[18] Huang, Cheng-Hui & Yin, Jian & Hou, Fang. (2011). A Text Similarity Measurement Combining Word Semantic Information with TF-IDF Method. Chinese Journal of Computers. 34. 856-864. 10.3724/SP.J.1016.2011.00856.

[19] Javed, Umair & Shaukat, Kamran & Hameed, Ibrahim & Iqbal, Farhat & Mahboob Alam, Talha & Luo, Suhuai. (2021). A Review of Content-Based and Context-Based Recommendation Systems. International Journal of Emerging Technologies in Learning (iJET). 16. 10.3991/ijet.v16i03.18851.

[20] Keshava, M. & Reddy, P. & Srinivasulu, S. & Naik, B.. (2020). Machine Learning Model for Movie Recommendation System. International Journal of Engineering Research and. V9. 10.17577/IJERTV9IS040741.

[21] Klimashevskaia, Anastasiia & Jannach, Dietmar & Elahi, Mehdi & Trattner, Christoph. (2023). A Survey on Popularity Bias in Recommender Systems. 10.48550/arXiv.2308.01118.

[22] Koren, Y., Bell, R., Volinsky, C. (2009). Matrix Factorization Techniques for Recommender Systems.

[23] Lam, X.N., Vu, T., Le, T.D., & Duong, A.D. (2008). Addressing cold-start problem in recommendation systems. International Conference on Ubiquitous Information Management and Communication.

[24] Lan, Fei. (2022). Research on Text Similarity Measurement Hybrid Algorithm with Term Semantic Information and TF-IDF Method. Advances in Multimedia. 2022. 1-11. 10.1155/2022/7923262.

[25] Li, Qing & Kim, Byeong. (2003). An approach for combining content-based and collaborative filters. 17-24. 10.3115/1118935.1118938.

[26] Liu, Haifeng & Hu, Zheng & Mian, Ahmad & Tian, Hui & Zhu, Xuzhen. (2014). A new user similarity model to improve the accuracy of collaborative filtering. Knowledge-Based Systems. 56. 156–166. 10.1016/j.knosys.2013.11.006.

[27] Lops, Pasquale & de Gemmis, Marco & Semeraro, Giovanni. (2011). Content-based Recommender Systems: State of the Art and Trends. 10.1007/978-0-387-85820-3_3.

[28] lu, Yu & Yu, Shoou-I & Chang, Tsung-Chieh & Hsu, Jane. (2009). A Content-Based Method to Enhance Tag Recommendation. 2064-2069.

[29] Maake, Benard & Zuva, Tranos. (2018). A Comparative Analysis of Text Similarity Measures and Algorithms in Research Paper Recommender Systems. 10.1109/ICTAS.2018.8368766.

[30] Mohd, Abdul & Hameed, Mohd & al Jadaan, Omar & Sirandas, Ramachandram. (2012). Collaborative Filtering Based Recommendation System: A survey. International Journal on Computer Science and Engineering. 4.

[31] Musa, Aminu & Haruna, Khalid & Ibrahim Jibia, Fa'Iz & Yunusa, Zayyanu & Ibrahim, Yakubu. (2021). Location-Aware Recommender System: A review of Application Domains and Current Developmental Processes. SINTECH (Science and Information Technology) Journal. 2. 10.31763/sitech.v2i1.610.

[32] Nguyen, Van-Doan & Sriboonchitta, Songsak & Huynh, Van-Nam. (2017). Using Community Preference for Overcoming Sparsity and Cold-Start Problems in Collaborative Filtering System Offering Soft Ratings. Electronic Commerce Research and Applications. 26. 101-108. 10.1016/j.elerap.2017.10.002.

[33] Panda, Deepak & Ray, Sanjog. (2022). Approaches and algorithms to mitigate cold start problems in recommender systems: a systematic literature review. Journal of Intelligent Information Systems. 59. 1-26. 10.1007/s10844-022-00698-5.

[34] Papadakis, Harris & Papagrigoriou, Antonis & Kosmas, Eleftherios & Panagiotakis, Costas & Markaki, Smaragda & Fragopoulou, Paraskevi. (2023). Content-Based Recommender Systems Taxonomy. Foundations of Computing and Decision Sciences. 48. 211-241. 10.2478/fcds-2023-0009.

[35] Polatidis, Nikolaos & Georgiadis, Christos. (2015). A multi-level collaborative filtering method that improves recommendations. Expert Systems with Applications. 48. 10.1016/j.eswa.2015.11.023.

[36] Prando, Alan & Contratres, Felipe & Souza, Solange N A & Souza, Luiz. (2017). Content-based Recommender System using Social Networks for Cold-start Users. 181-189. 10.5220/0006496301810189.

[37] Rahman, Md. Mijanur & Shama, Ismat & Rahman, Siamur & Nabil, Rahmatullah. (2022). Hybrid Recommendation System to Solve Cold Start Problem. Journal of Theoretical and Applied Information Technology. 100.

[38] Reshak, Kaiser & Dhannoon, Ban & Sultani, Zainab. (2023). Hybrid recommender system based on matrix factorization. AIP Conference Proceedings. 2457. 40010. 10.1063/5.0118335.

[39] Salmani, Sakina & Kulkarni, Sarvesh. (2021). Hybrid Movie Recommendation System Using Machine Learning. 1-10. 10.1109/ICCICT50803.2021.9510058.

[40] Sarwar, Badrul & Badrul, & Karypis, George & Cybenko, George & Konstan, & Joseph, & Reidl, & Tsibouklis, John. (2001). Item-based collaborative filtering recommendation algorithmus.

[41] Shen, Jian. (2013). Collaborative Filtering Recommendation Algorithm Based on Two Stages of Similarity Learning and Its Optimization. IFAC Proceedings Volumes. 46. 335-340. 10.3182/20130708-3-CN-2036.00068.

[42] Son, Jieun & Kim, Sb. (2017). Content-Based Filtering for Recommendation Systems Using Multiattribute Networks. Expert Systems with Applications. 89. 10.1016/j.eswa.2017.08.008.

[43] Son, L.H. (2016). Dealing with the new user cold-start problem in recommender systems: A comparative review. Inf. Syst., 58, 87-104.

[44] Volkovs, Maksims & Yu, Guang Wei & Poutanen, Tomi. (2017). Content-based Neighbor Models for Cold Start in Recommender Systems. 1-6. 10.1145/3124791.3124792.

[45] Wang, Donghui & Liang, Yanchun & Xu, Dong & Feng, Xiaoyue & Guan, Renchu. (2018). A Content-Based Recommender System for Computer Science Publications. Knowledge-Based Systems. 157. 10.1016/j.knosys.2018.05.001.

[46] Yuan, Hongli & Hernandez, Alexander. (2023). User Cold Start Problem in Recommendation Systems: A Systematic Review. 10.1109/ACCESS.2023.3338705.

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