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Product Recommendation System: A Systematic Literature Review

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Abstract: ***In today's world, we find a wide variety of search options and we may have difficulty selecting what we really need. The recommendation System plays an important part in dealing with these problems. A recommender system is a framework that is a filtering system that filters the data with various algorithms and recommends the user with the most relevant data. Recommendation systems are productive customization mechanisms, often up-to-date and recommendations based on current consumer preferences. These systems have shown to be extremely helpful in different areas of e-commerce, education, movies, music, books, films, scientific papers, and various products. This paper reviews many approaches of recommendation techniques with their upsides and downsides and diverse performance measures. We have reviewed various articles, analyzed their technique and approach, major features of the algorithm utilized, and potential areas for improvement in that research work.***
Keywords: Recommendation system, collaborative, hybrid, content-based, machine learning

I. INTRODUCTION

In the latest development in the digital economy, the improved engagement between the organizations and their customers has become a core element of the marketing landscape and companies face the challenges of supplying customers with differentiated goods and services based on customer knowledge [7], [52]. As the volume of data collected on the internet rises, more information would be presented to users. However, this wealth of knowledge allows consumers to make a more focused effort when choosing their products [10], [53]. This issue is particularly important for the e-commerce sector. Personalization is the terminology that adequately describes this phenomenon [48]. Salina et al. [1] state that companies are able to retain their strong associations with consumers and increase customer satisfaction by differentiated personalized services. And personalization of the web content can be used to save time and expense for the content search and as a tool to increase sales by increasing user satisfaction with the site. Various recommending mechanisms for higher customer satisfaction make this personalization possible [8]. This system operates in two different stages, first analyzing the user's preference for a product, and then trying to locate a similar collection of objects in which the user may be interested. In addition, this leads to better product decisions [33], [41], [46]. One. Bang et al. [4] for assessing the products with an outstanding assessment of the buying criterion they employed the purchasing criteria chosen by the consumer, and product ratings created by the consumers who bought the goods and then arranged the best ten products and recommended them to the user. The consumer will select and customize the details for that individual by representing the selection-criteria in the analysis [34], [47].

An information extraction method that helps to locate the rating or customer preference for a specific object is a subcategory of the recommender system [42]. Many choices can be made by considering specific recommendations such as what to buy, style of music to listen to or what to read online news.

Two categories of information related to the recommendation systems:

1) User-item interactions consisting of ratings information, user preferences, etc.
2) Characteristics Information metrics consisting of information about the objects/products such as keywords, categorization, user's profile, etc.

Basically it is a filtering mechanism in general and we have three major categories of recommending systems shown in fig 1.1.

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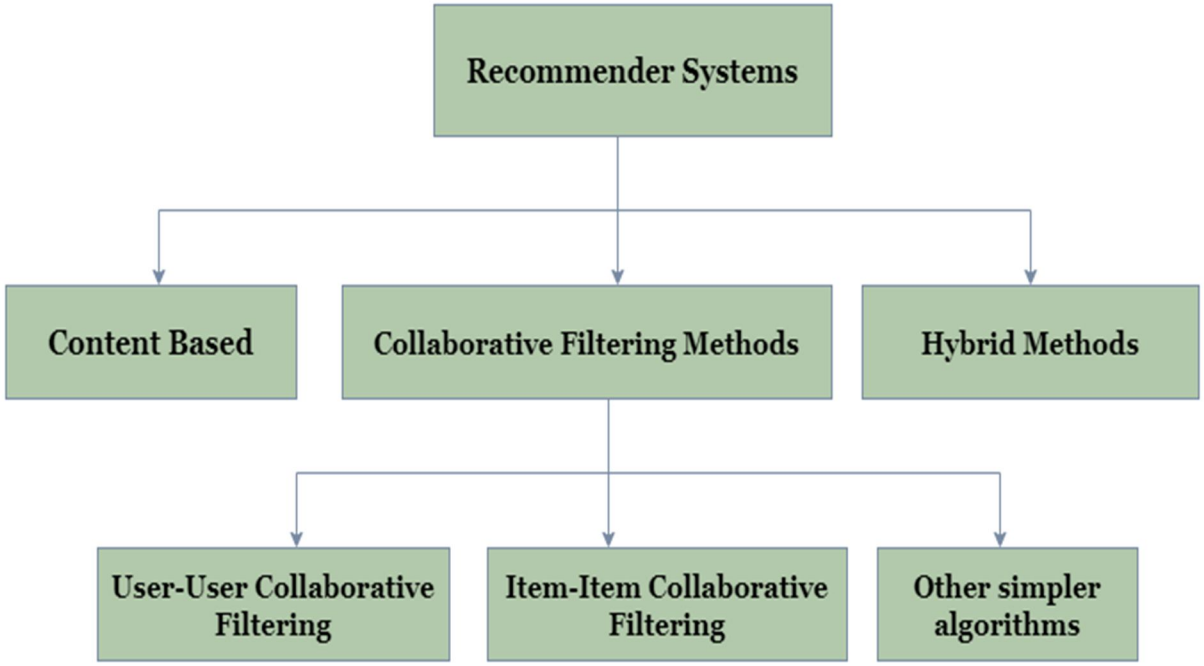


Fig 1.1 Different recommendation system

Product-recommendation system is powered by machine learning and employs suggestions of goods associated with a brand's digital assets. Driven by a range of algorithmic decisions, recommendations algorithms have a customized experience for user, product and background information both on-site as well as off-site [24], [35]. This helps people find what they want and even don't know the items they're searching for thus improving the search process. In this way, enterprises can understand more about the individual needs and desires of a customer optimize success in real time while improving their long-term research roadmaps [11], [23].

It is also a reality that the user's preferences alter constantly. That is the reason for the recommendation system. So, that for the organizations selling the products to be profitable, it is possible to decide the most likely product to be sold and the most unlikely product to be sold [45]. The recommended systems will now help us escape such uncertainty and make smarter decisions [9].

II. RELATED WORK

Salina et al. [1] worked on mining sentiment details from social user's-reviews as proposed through their recommendation model. They also developed a new connection, called interpersonal sentiment, which reflects the effect of users' friends on the users in a sentimental manner. They assess the user's sentiment quantitatively and use the items' sentiment distribution between users to assess the item's reputation. The results of their experiments show that the 3-sentimental factors significantly contribute to the rating prediction. It also demonstrates substantial changes in existing real world dataset approaches.

Yi et al [2] have worked towards designing an appropriate hybrid recommendations-system that can study, interpret the trend and predict consumer interest in the purchase of a specific product at a chosen shop from the data available for customer shopping by means of reviews. Mingxin et al. [3] suggested a new personalized approach for rating prediction in the product recommendation based on deep neural networks and multiview fusion, known as DeepFusion. Their model is able to integrate user-generated content and raw items in a unified space, including numeric-ratings, text-reviews and item metadata.

Wang et al. [5] proposed a customized recommendation system for e-commerce products based on the representation of learning clusters. They integrated RNN and attention mechanisms to design product recommendation-systems for e-commerce. Table 1 shows the methodology used, highlights of the paper and its technical gap.

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Table 1
Literature review

Sr. No.	Paper	Methodology	Highlights	Technical gap
1	E-commerce personalized recommendation analysis by deeply-learned clustering [5]	Customized recommendation system for e-commerce products based on the representation of learning clusters. They integrated RNN and attention mechanisms to design product recommendation systems for e-commerce(RNN with attention mechanism and KNN clustering).	1. They have proposed a novel e-commerce products recommendation system based on deep clustering methods, which can effectively solve data sparse and information overload problems. 2. The traditional kNN is improved to effectively select adjacent object sets.	1. Cold start problem and Sparsity problem can arise if there is no web browsing history.
2	DeepFusion: Fusing User-Generated Content and Item Raw Content towards Personalized Product Recommendation [3]	They developed user and product representations using numerical ratings, written reviews, and item metadata using DeepFusion, a deep neural network. They have also discussed item Metadata modeling.	1. The DeepFusion model outperformed all of the other models.	1. Model was evaluated on the basis of a single dataset.
3	Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review [2]	The collaborative filtering and product-product similarity methods are used in this paper to build a Hybrid-recommendation system.	1. When it comes to predicting customer purchase behaviour, there is no human interaction. 2. In terms of accurate prediction of customer attitude towards shopping a product in a certain shop, the Hybrid Recommendation System (HRS) clearly surpasses other contemporary algorithms.	1. Data and application are defined interoperability
4	Product Recommendation System from Users Reviews using Sentiment Analysis [1]	By manipulating key words, their model can anticipate the product's average score. To accomplish so, they have combined a fresh new relative model with the standard approach, which is a sentiment-based prediction strategy.	1. They created a new relationship between the user and their friends called "interpersonal sentiment" influence, which reflects how users' friends influence them from a sentimental standpoint.	1. They can take into account additional linguistic rules while interpreting the context. 2. Sentiment dictionaries can be enhanced to allow for finer grained sentiment analysis.
5	Product Recommendation System based on User Purchase Priority [4]	They've devised a system that considers the user's priority while looking for and purchasing goods. The system then shows the user the findings after processing and analysis of their preferences.	1. The user's preferences are taken into account so that the user can receive more relevant results.	1. Explicit feedback of user is required
6	Product Recommendation System based on User Trustworthiness & Sentiment Analysis [13]	Their suggested system collects reviews from various websites and conducts sentiment analysis and opinion mining on them. Other considerations include star ratings, buyer's profile and prior transactions, as well as whether or not the review was posted after the purchase.	1. In this methodology, the trustworthiness of the reviewer is checked.	1. Neural networks may be used to decrease over-fitting even further.

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7	Product Recommendation System Using Machine Learning [14]	NetSpam is a structure that employs spam characteristics to demonstrate review datasets as "heterogeneous information" frameworks in order to develop spam detection methods into a collection of issues in these networks.	1. Even without a prepared range, SpamDup can sort out the relevance of each feature, and it can operate more effectively throughout the process of expanding highlights than previous works with only a few highlights.	1. Using alternative supervisory techniques, such as the semi-managed approach, in the same way as other datasets, the vast majority of the weighted highlights have no quantifiable effect.
8	Improving the Product Recommendation System based-on Customer Interest for Online Shopping Using Deep Reinforcement Learning [15]	The product recommendation system leverages the reinforcement learning approach to increase the recommendation system's quality by providing better and more related choices based on click patterns and user profile information.	1. They showed that reinforcement learning is more effective than other methods.	1. Cold start problems may arise if the user's data is missing.
9	A Study on the effect of product recommendation system on customer satisfaction: focused on the online shopping mall [16]	The method of survey was utilized to record in a manner that the respondents were chosen for the study and distributed 300 questionnaires provided with proper personal care and the researchers gathered all the questionnaires.	1. The product recommendation system's characteristics have a good influence on customer satisfaction and thus customer requirements need to be satisfied on the basis of quality surveys.	1. Further analysis on various factors is needed. 2. Survey was conducted on a small scale that needs to be increased.
10	Flipkart Product Recommendation System [17]	They have used Hybrid Content-Collaborative Based Filtering and have represented a system which will recommend products to the user based on the customer reviews.	1. Using recommendation algorithms, systems can identify the most often purchased goods by consumers and recommend them to other customers or users.	1. Cold start problems may arise if review of a particular product is not available.

III. RECOMMENDATION SYSTEM TECHNIQUES

Recommendation systems are classified on the basis of problem domain, information used and prediction algorithm. They are content-based RS, collaborative filtering and hybrid approaches as illustrated in fig1.1.

A. Content-Based Recommendation system

The system learns to make suggestions based on the previous responses submitted by the user by evaluating the feature similarities between the items. The user profile based on historical data of previously rated items is generated by a Content based recommendation system [26]. A user profile reflects the interests of the user and is also able to adapt to new interests. User profile is matched with the content object's features and is essentially the mechanism of recommendation. A decision indicating the user's interest in the item results from this procedure [32], [44]. Content-based recommendation system is mentioned in Fig 1.2.

B. Collaborative-filtering Recommendation System

The approach is typically used to capture and analyze user's actions, interests or preferences information and determine what they want based on their similarities to other users [18]. One important benefit of a collective filtering approach is the ability to reliably suggest complex objects like films without the need of "understanding" the product itself. This approach does not focus on computer analyzable information. Collaborative filters rely on the premise that parties who have agreed in the past agree in the future and prefer related things in the past. For example, if a person A likes item 1, 2, 3 and B, it's equivalent to 2,3,4; and A would like item 4 and B would like item 1 [25]. Collaborative filtering system is mentioned in Fig 1.2.

Collaborative filtering can be further divided into 3 categories:

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1) *User-User Collaborative Filtering:* Model is looking for lookalike buyers and offering items focused on the choices made by its lookalike [37]. This is a highly efficient and at the same time consuming algorithm. This method of filtering includes any pair of consumer details that takes time to be computed. This algorithm is difficult to implement for large base platforms [55].
2) *Item-Item Collaborative Filtering:* It is similar to the above algorithm, but the Model aims to look at the item in the same way instead of finding a consumer look. After the model has a matrix that looks the same, it can conveniently advise a customer who has bought every object in the shop [36], [50]. This algorithm takes far less resources than collaborative filtering between user and user. The algorithm takes much less time for a new customer than it does for the user-user collaborative filtering as all similarity values among customers are not necessary. In its recommendation engine, Amazon uses this strategy to present similar goods that enhance sales [20], [28].
3) *Other Simpler Algorithms:* Other methods, such as basket analysis, are not typically more strongly predictive than the algorithms outlined above [21], [22], [49].

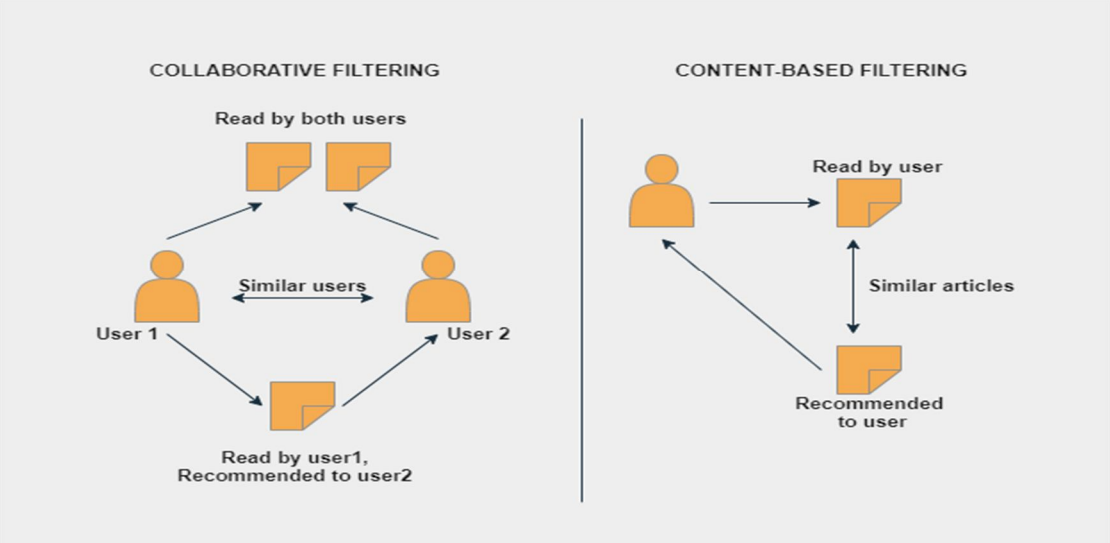


Fig 1.2 Collaborative filtering and content-based recommendation system [12]

C. Hybrid Recommendation System

New studies have shown that it can be more efficient to combine collective and content-based recommendations. Hybrid methods can be applied by independently making and then integrating content-based and collaborative predictions [19]. In addition, it adds content based capabilities to a collaborative approach and vice-versa; or it integrates methods into a single paradigm [30], [31]. Several trials have been carried out to compare the hybrid's success with pure content-based and collaborative techniques. They show that hybrid methods can be more precise than pure approaches. Such approaches may be used to solve typical challenges, such as cold start or data paucity, in recommendation systems. Netflix's use of hybrid recommendation systems is a prime example. The website recommends by comparing the viewing and browsing behaviors (i.e. collaborative filtering) of similar users as well as by offering movies which share features with highly rated movies (content-based filtering) [27], [43]. Fig 1.3 represents hybrid recommendation system.

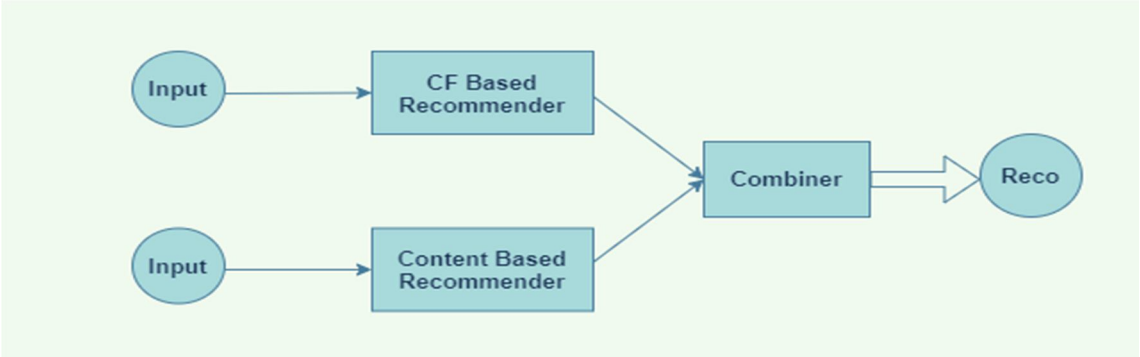


Fig 1.3 Hybrid Recommendation System

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IV. STRATEGIES BEHIND THE RECOMMENDER-SYSTEMS

Recommendations can be important insights and an ability to learn more adequately to satisfy user needs, increase revenue and strengthen a brand's overall relationship. The approaches to the recommendation system can be categorized into three major categories as mentioned in Fig 1.4. Any of these approaches determines which products are involved in an experience. In choosing a strategy for use, brands must first estimate the amount of available customer and product knowledge and position in the buying funnel to determine which strategy to use.

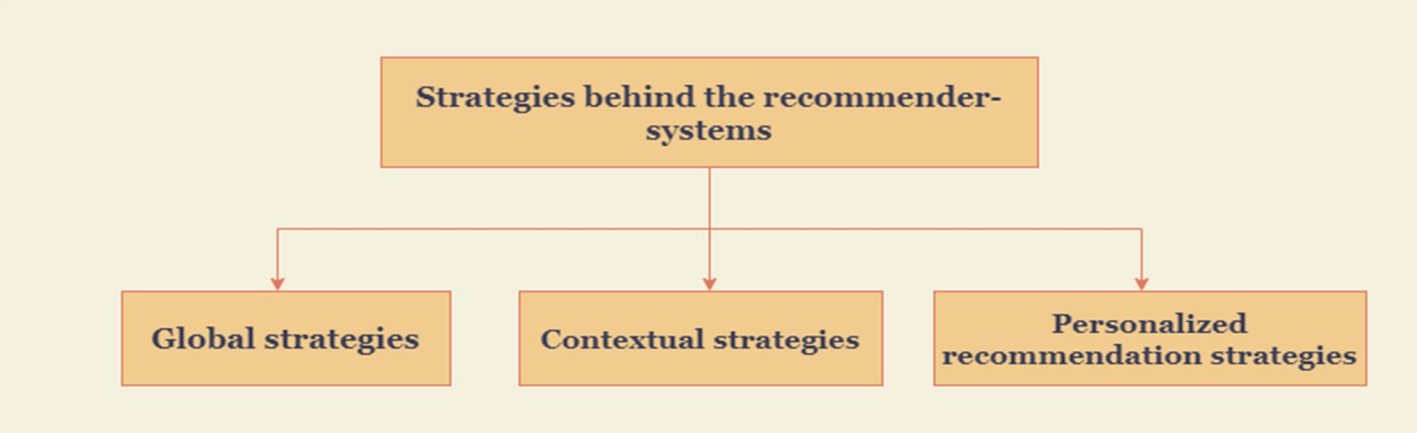


Fig 1.4 Strategies behind the recommender-systems

A. Global strategies

This strategy is the simplest to implement, including a recommendation that clearly serves any consumer both well-known and unfamiliar – of the most commonly bought, common or trendy brands.

B. Contextual strategies

This strategy is based on product context and evaluates product characteristics such as shape, color, category and the frequency at which goods are bought for shoppers to suggest products.

C. Personalized recommendation strategies

The most advanced personalized tactics of the levels not only heed the context, but also the actual behavior. They take into account the available usage data and the product background for each particular user's surface suggestions [51]. This ensures that a brand has access to consumer behavioral information such as add-to-carts, purchase history, clicks, affinities and more to introduce customers effectively. Example of strategies behind the recommender-systems is mentioned in Fig 1.5.

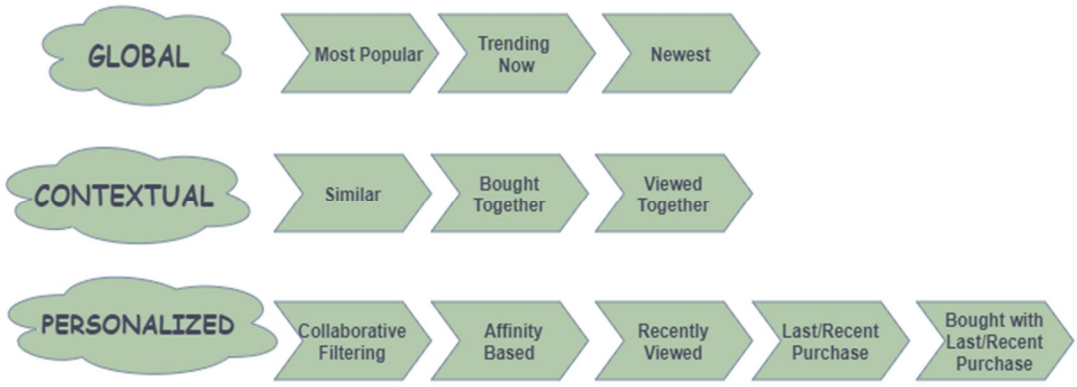


Fig 1.5 Examples of Strategies behind the recommender-systems

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V. CHALLENGES FACES IN RECOMMENDATION SYSTEM

Even though recommendation engines generate a great deal of money for giants like Amazon and Netflix, they face different challenges. Some of the following are mentioned below [6]:

A. Synonymous Names

Synonymy is challenging where a particular product or feature has a similar meaning with two or more different names or listings (for example action or action films). In this case, the recommendation method cannot determine if the terms contain different items or the same 'item'.

B. Scalability

The scalability of algorithms that have real-world databases is another problem with the recommendation systems. The standard solution is in most cases overloaded with a multitude of products and customers leading to problems in the data set and a decrease in efficiency.

C. Latency Challenges

Latency problems occur when new items are added to a recommendation engine platform more frequently. Nevertheless, consumers are recommended for current products because new products have not been rated. In combination with the interaction of the user-item, companies may either use a collaborative filtering method or the category-based method.

D. Privacy

In most cases, consumers must provide their personal information with customized and useful resources through the referral framework [54]. It does, however, lead to numerous privacy and security problems and makes consumers feel unable to incorporate their personal data into recommendation systems. However, since the Recommendation Framework is bound to provide consumer personal data and use it to provide personalized recommendations, it must take proper care of the issues to maintain trust among its customers [38], [39].

E. Issue of Sparsity

In some cases consumers do not rate or review the products they buy, so that the rating and review model is comparatively sparse and leads to data sparsity problems. The ability of the model to find a number of users with common ratings or preferences is reduced. A solution to this issue is mentioned in [29], [40].

VI. CONCLUSION

In this paper, we have reviewed various articles, analyzed their technique and approach, and major features of the algorithm utilized. Then we discussed the related research work done in the same. From the study done we can infer that the "products" and the "quality" of the recommendations given by the engine are all the most important concerns of the users and buyers. Such cognitive computing techniques will lead to the next stage of quality of the recommenders. Recommendation algorithms are typically created and built to make recommendations based on popular products. However, it should not be limited to that. It should offer variety because the same and well-known things can bore customers. As a result, there may be a higher level of precision by working on potential areas for improvement as mentioned in our paper.

REFERENCES

[1] Salina, Adinarayana & Rao, K. & Murthy, G.. (2017). Product Recommendation System from Users Reviews using Sentiment Analysis. International Journal of Computer Applications. 169. 30-37. 10.5120/ijca2017914585.
[2] Yi, S., Liu, X. Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review. Complex Intell. Syst. 6, 621–634 (2020). https://doi.org/10.1007/s40747-020-00155-2.
[3] Mingxin Gan, Hang Zhang, "DeepFusion: Fusing User-Generated Content and Item Raw Content towards Personalized Product Recommendation", Complexity, vol. 2020, Article ID 4780191, 12 pages, 2020. https://doi.org/10.1155/2020/4780191.
[4] One. Bang J, Hwang D, Jung H. Product Recommendation System based on User Purchase Priority. Journal of Information and Communication Convergence Engineering [Internet]. 2020 Mar 31;18(1):55--60. Available from: https://doi.org/10.6109/JICCE.2020.18.1.55 .
[5] Kai Wang, Tiantian Zhang, Tianqiao Xue, Yu Lu, Sang-Gyun Na, E-commerce personalized recommendation analysis by deeply-learned clustering, Journal of Visual Communication and Image Representation, Volume 71, 2020, 102735, ISSN 1047-3203,

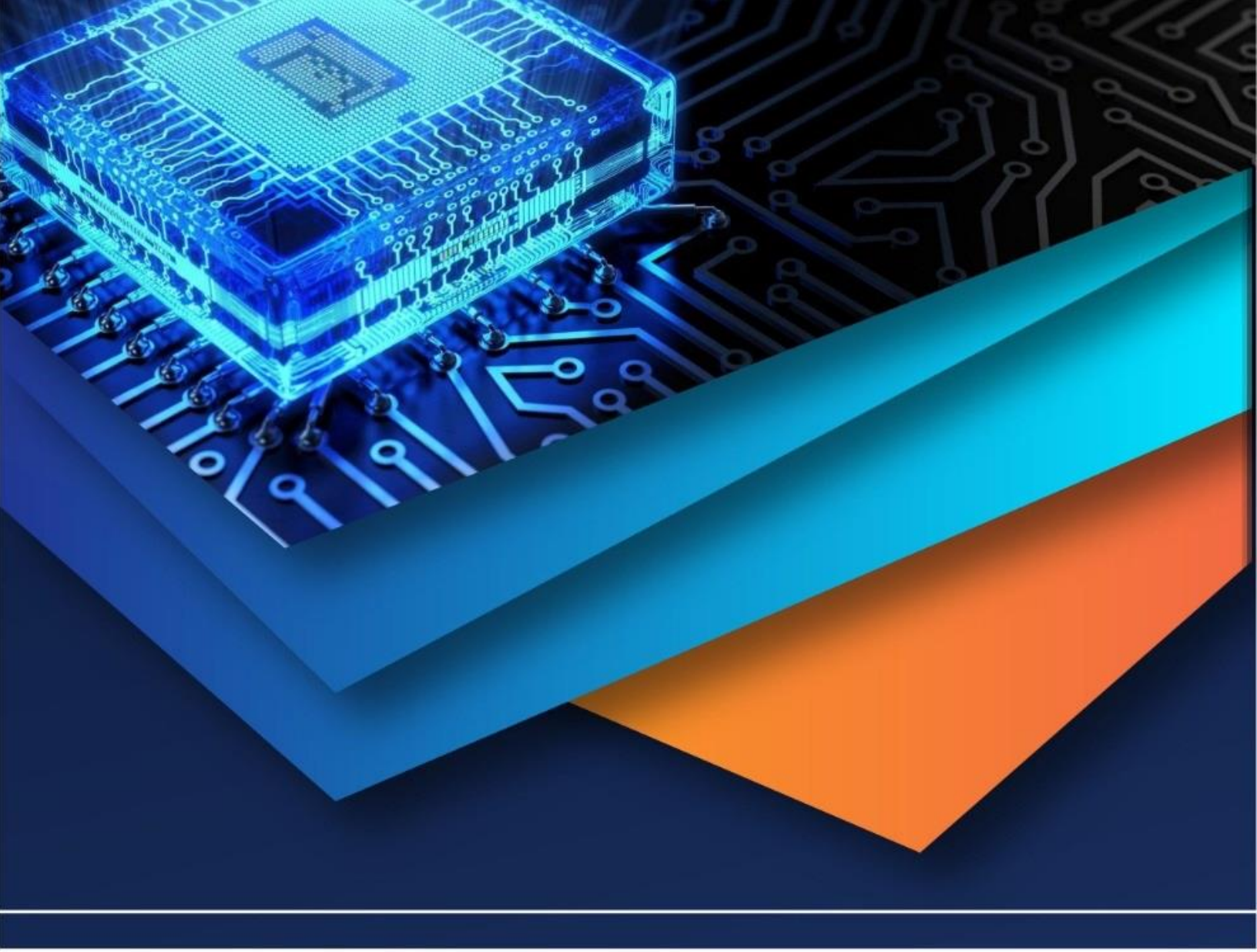
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[6] https://doi.org/10.1016/j.jvcir.2019.102735.Kumar, P., Thakur, R.S. Recommendation system techniques and related issues: a survey. Int. j. inf. tecnol. 10, 495–501 (2018). https://doi.org/10.1007/s41870-018-0138-8.
[7] Jatin Sharma and Kartikay Sharma and Kaustubh Garg and Avinash Kumar Sharma, Product Recommendation System a Comprehensive Review, IOP Conference Series on Materials Science and Engineering, volume 1022, 2021, https://doi.org/10.1088/1757-899x/1022/1/012021.
[8] Allen, C., Kania, D., & Yaeckel, B. (1998). Internet world guide to one-to-one web marketing. New York: Wiley.
[9] Salina, Adinarayana & Rao, K. & Murthy, G.. (2017). Product Recommendation System from Users Reviews using Sentiment Analysis. International Journal of Computer Applications. 169. 30-37. 10.5120/ijca2017914585.
[10] A. A. Lenskiy and E. Makita, "Bayesian approach to users' perspective on movie genres," Journal of Information and Communication Convergence Engineering, vol. 15, no. 1, pp. 43-48, 2017.
[11] P. V. Kulkarni, R. Phatak, B. Bhate, R. Deshpande and S. Rai, "Recommendation System for Enhancing eLearning using Deep Learning," 2019 IEEE Pune Section International Conference (PuneCon), 2019, pp. 1-4, doi: 10.1109/PuneCon46936.2019.9105685.
[12] Kulkarni P.V., Rai S., Kale R. (2020) Recommender System in eLearning: A Survey. In: Bhalla S., Kwan P., Bedekar M., Phalnikar R., Sirsikar S. (eds) Proceeding of International Conference on Computational Science and Applications. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-15-0790-8_13.
[13] Product Recommendation System based on User Trustworthiness & Sentiment Analysis Gunjeet Kaur Soor, Amey Morje, Rohit Dalal, Deepali Vora ITM Web Conf. 32 03030 (2020) DOI: 10.1051/itmconf/20203203030.
[14] Pawar, Sanket Hanmant, Avadhut Prashant Lohar, Omkar Nitin Thopate, Rushikesh Sukhdev Auti, and Y. B. Gurav. "PRODUCT RECOMMENDATION SYSTEM USING MACHINE LEARNING." INTERNATIONAL JOURNAL 6, no. 4 (2021)
[15] Shahbazi, Zeinab, and Yung-Cheol Byun. "Improving the Product Recommendation System based-on Customer Interest for Online Shopping Using Deep Reinforcement Learning." (2021).
[16] CHO, Ba-Da, Rajasekhara Mouly POTLURI, and Myoung-Kil YOUN. "A Study on the Effect of Product Recommendation System on Customer Satisfaction: Focused on the Online Shopping Mall". 산경연구논집 11, no. 2 (February 28, 2020): 17–23. doi:10.13106/JIDB.2020.VOL11.NO2.17
[17] Keerthana, T., T. Bhavani, N. Suma Priya, V. Sai Prathyusha, and K. Santhi Sri. "Flipkart Product Recommendation System." transactions 33 (2020): 34.
[18] Elahi M, Ricci F, Rubens N (2016) A survey of active learning methods in collaborative filtering recommender systems. Comput Sci Rev 20:29–50.
[19] Nouh RM, Lee H-H, Lee W-J, Lee J-D (2019) A smart recommender based on hybrid learning methods for personal well-being services. Sensors 19(431):1790–1801.
[20] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl,"Item Based collaborative filtering recommendation algorithms", WWW10, May 1-5, 2001, Hong Kong.
[21] Wang, Xiangyu, et al. "Semantic-based location recommendation with multimodal venue semantics." IEEE Transactions on Multimedia 17.3 (2015): 409-419.
[22] M. Jiang, P. Cui, F. Wang, W. Zhu, S. Yang, "Scalable recommendation with social contextual information".
[23] James Davidson, et al., The YouTube video recommendation system, in: Proceedings of the Fourth ACM Conference on Recommender Systems, ACM, 2010, pp. 293–296.
[24] David W. McDonald, Mark S. Ackerman, Expertise recommender: a flexible recommendation system and architecture, in: Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work, ACM, 2000, pp. 231– 240.
[25] X. Zhang, X. Jiang, Collaborative filtering algorithm based on user attribute item dependency, in: IEEE International Conference on Communication Software and Networks, IEEE, 2017, pp. 1426–1431.
[26] Ting Chen et al., Content recommendation system based on private dynamic user profile, in: 2007 International Conference on Machine Learning and Cybernetics, IEEE, 2007, pp. 2112–2118.
[27] Xin Jin, Yanzan Zhou, Bamshad Mobasher, A maximum entropy web recommendation system: combining collaborative and content features, in: Proceedings of the eleventh ACM SIGKDD international conference on Knowledge discovery in data mining, ACM, 2005, pp. 612–617.
[28] L. Wu, C. Quan, C. Li, Q. Wang, B. Zheng, and X. Luo, "A context-aware user-item representation learning for item recommendation," ACM Transactions on Information Systems, vol. 37, no. 2, pp. 1–29, 2019.
[29] X. Ma, X. Lei, G. Zhao, and X. Qian, "Rating prediction by exploring user's preference and sentiment," Multimedia Tools and Applications, vol. 77, no. 6, pp. 6425–6444, 2018.
[30] M. Alfarhood and J. Cheng, "DeepHCF: a deep learning based hybrid collaborative filtering approach for recommendation systems," in Proceedings of the 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), IEEE, Orlando, FL, USA, pp. 89–96, December 2018.
[31] D. Kim, C. Park, J. Oh, and H. Yu, "Deep hybrid recommender systems via exploiting document context and statistics of items," Information Sciences, vol. 417, pp. 72–87, 2017.
[32] S. Li, J. Kawale, and Y. Fu, "Deep collaborative filtering via marginalized denoising auto-encoder," in Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, ACM, Melbourne, Australia, pp. 811–820, October 2015.
[33] B. Xiao and I. Benbasat, "E-commerce Product Recommendation Agents: Use, Characteristic, and Impact" MIS quarterly, vol. 31, no. 1, pp.137-209, 2007. DOI: 10.2307/25148784.
[34] J. Y. Choeh, S. K. Lee, and Y. B. Cho, "Applying rating score's reliability of customers to enhance prediction accuracy in recommender system," Journal of The Korea Contents, vol. 13, no. 7, pp. 379-385, 2013. DOI:10.5392/jkca.2013.13.07.379.
[35] Shahbazi, Z.; Hazra, D.; Park, S.; Byun, Y.C. Toward Improving the Prediction Accuracy of Product Recommendation System Using Extreme Gradient Boosting and Encoding Approaches. Symmetry 2020, 12, 1566.
[36] Zhang, Z.P.; Kudo, Y.; Murai, T.; Ren, Y.G. Enhancing recommendation accuracy of item-based collaborative filtering via item-variance weighting. Applied Sciences 2019, 9, 1928.
[37] De Meo, P.; Fotia, L.; Messina, F.; Rosaci, D.; Sarné, G.M. Providing recommendations in social networks by integrating local and global reputation. Information Systems 2018, 78, 58–67.
[38] Ch. Xu and J. Zhang," Combating product review spam campaigns via multiple heterogeneous pairwise features", In SIAM International Conference on Data Mining, 2014.

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[39] B. Viswanath, M. Ahmad Bashir, M. Crovella, S. Guah, K. P. Gummadi, B. Krishnamurthy, and A. Mislove, "Towards detecting anomalous user behavior in online social networks", In USENIX, 2014.
[40] E. D. Wahyuni , A. Djunaidy," Fake Review Detection From a Product Review Using Modified Method of Iterative Computation Framework", In Proceeding MATEC Web of Conferences, 2016.
[41] Chin-Hui Lai,Duen-Ren Liu,Siao-Rong Lin,"Document Recommendation with implicit feedback based on matric factorization and topic model",Proceedings of IEEE International Conference on Applied System Innovation 2018.
[42] Francesco Ricci, Lior Rokach, Bracha Shapira and Paul B. Kantor, "Recommender Systems Handbook," Springer, ISBN: 978-0-387- 85819-7, ©Springer Science + Business Media LLC, 2011.
[43] Yu Liu, Shuai Wang, M. Shahrukh Khan, and Jieyu He," A Novel Deep Hybrid Recommender System Based on Auto-encoder with Neural Collaborative Filtering", Big Data Mining and Analytics,ISSN, 2096-0654 03/06,pp211– 221, Volume 1, Number 3, September 2018.
[44] Gang Wu, Viswanathan Swaminathan, Saayan Mitra and Ratnesh Kumar,"Digital Content Recommendation System Using Implicit Feedback Data",IEEE International Conference on Big Data 2017.
[45] Driskill, R. & Riedl, J., 1999. Recommender Systems for E-Commerce: Challenges and Opportunities. American Association for Artificial Intelligence, pp.73–76. Available at: http://aaaipress.org/Papers/Workshops/1999/WS-99-01/WS99-01-012.pdf.
[46] L.C. Wang, X.Y. Zeng, L.Koehl, and Y. Chen "Intelligent fashion recommender system: Fuzzy logic in personalized garment design," IEEE Transactions on Human-Machine Systems, vol.45 no.1 pp 95-109, 2015.
[47] Adomavicius G, Tuzhilin A (2005) Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Trans Knowl Data Eng 17(6):734–749
[48] Sarwar B, Karypis G, Konstan J, Riedl J (2000) Analysis of recommendation algorithms for e-commerce. In: Proceedings of the 2nd ACM conference on Electronic and commerce, pp 158–167.
[49] Rodrigues CM, Rathi S, Patil G (2016) An efficient system using item and user-based CF techniques to improve recommendation. In: Proc. of International Conf. on next generation computing technologies (NGCT), pp 569–574.
[50] Deshpande M, Karypis G (2004) Item-based top-N recommendation algorithms. ACM Trans Inf Syst 22(1):143–177.
[51] Ji K, Shen H (2014) Using category and keyword for personalized recommendation: a scalable collaborative filtering algorithm. In: Proc. of sixth international symposium on parallel architectures, algorithms and programming, Beijing, pp 197–202.
[52] Sharma L, Gera A (2013) A survey of recommendation system: research challenges. Int J Eng Trends Technol 4(5):1989–1992.
[53] Yu, W.; Zhang, H.; He, X.; Chen, X.; Xiong, L.; Qin, Z. Aesthetic-based clothing recommendation. Proceedings of the 2018 World Wide Web Conference, 2018, pp. 649–658.
[54] Sergelen D., Park, Y. S., & Lee, D. S. (2019). The Effect of Trust in Online Shopping Mall and Trust in Recommendation System on Cross-Purchase Intention. The Articles of the Korean Industrial Engineering Society's Spring Joint Conference, 4, 4821-4834.
[55] Lee, S. J., & Lee, H. C. (2007). A Study on Prediction Performance of Correspondence Average Algorithm in Cooperative Filtering Recommendation. Information System Review, 9(1), 85-103.

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