An Exhaustive Study on Context based Recommender Systems

Shubham Mastkar
Student
Shri Govindram Seksaria Institute of Technology and Science, Indore, India

Urjita Thakar
Professor
Shri Govindram Seksaria Institute of Technology and Science, Indore, India

ABSTRACT
Enormous amount of digital information has made it increasingly challenging to identify the relevant information for users. Recommender systems were introduced to solve this problem by providing personalized recommendations to users. Context-based recommender systems are recent which uses contextual information to provide more personalized recommendations. In this paper, an exhaustive study of context-based recommender systems has been presented. The key concepts and various approaches used in context-based recommender systems have been discussed. Various application areas have also been presented.

Keywords
Context-Based Recommender Systems, Personalized Recommendations, Contextual Information, Approaches in Recommender Systems, Recommender System Application Areas.

1. INTRODUCTION
These days, enormous amount of information is available online. Due to the overload of available information, users have to spend lot of time and energy to find useful content. Recommendation systems have now became an important part of many online platforms, including e-commerce sites, streaming services, and social media platforms. They offer personalised and appropriate recommendations to customers in order to assist them to browse through the large amounts of information and products available online. Traditional recommendation systems used different approaches for recommendation such as collaborative filtering [1], content-based filtering [2] and hybrid methods [3]. They have been successful in providing personalized recommendations to some extent. Context of a user can give better insights of current situation of a person. However, traditional recommender systems tend to ignore the context in which the recommendations are being made, which can lead to irrelevant or even incorrect recommendations. [4]

Context-based recommendation systems aim to address these limitations by utilizing context information and making more appropriate recommendations. A users context may in- clude information such as user location, browsing history, and preferences, item context such as item features, reviews, and ratings, and social context such as social network information and user interactions. By considering these different types of context, context-based recommendation systems can provide more accurate and relevant recommendations. [5]

In this work therefore a study has been presented on available literature to provide an insight into the current trend of research in context-based recommendation systems. We begin by defining what context is in the context of recommendation systems and how it differs from traditional recommendation systems. Different contexts that are usually utilized in recommendation systems are discussed. The various methods that have been proposed for incorporating context into recommendation systems have also been discussed.

1.1 The paper is organized as follows –
In Section 2, the traditional recommender system have been discussed. The traditional methods and their limitations have been presented. In section 3, Context bases recommender systems and its various types have been discussed. In section 4, the approaches for context aware recommender systems and their applications have been presented. In section 5 various challenges associated with context based recommender systems have been discussed. The paper has been concluded in section 6.

2. TRADITIONAL RECOMMENDER SYSTEMS
Recommender systems have been a significant area of research in the field of artificial intelligence for several decades. A recommender system's purpose is to provide users customized suggestions based on their interests, preferences, and behaviour. The rise of the internet and digital content has created a huge demand for recommender systems [6], as users are faced with an overwhelming amount of information and choices. [7]

Three major types of filtration techniques have been used in past for recommendation these are,

1) Content-based filtering.

2) Collaborative filtering.

3) Hybrid filtering methods.

A detailed description of these methods is given in next subsections.

2.1 Content-based filtering
It uses the different contents of a single user such as his past purchase history, rated items or history of personal videos viewing, tv programs, types of movies etc. Contents generated by the user is used for recommendation. It works on principle that if a user has liked some content or consumed some product then it is more likely that user might like the similar product in future. In this method user's previous history is analyzd and accordingly recommendations are made. For example, if a user likes action movies, a content-based recommender system can recommend similar action movies based on the genre, director, and actors [8]. Since it uses history of user to recommend, it is not suitable for new users who do not have past history. This problem is known as cold start problem [2].

2.2 Collaborative filtering
As the name suggests collaborative filtering utilizes

preferences of multiple users to make recommendation. It uses the concept that if some group of users have similar interests then they may have similar choices. One persons preference may get influenced by other persons preference. This method has been used in many areas such as E-commerce [9], social networking [10] and Movie or music streaming services [11] [12]. Collaborative filtering approach also face problems like cold start problem when new users do not have any activity. It also suffers from problem of filter bubble effect [13] in which if users are exposed only to small number of options then they do not get recommendation on new ideas [1].

2.3 Hybrid Methods

In hybrid methods both content based and collaborative filtering methods are combined according to make recommendations. Hybrid methods can take advantage of the strengths of both methods and overcome their weaknesses [14] [15]. For example, if a user has not given rating to some items, a hybrid recommender system can use content-based filtering to generate recommendations based on preferences used by other similar users. [3]

According to Aditya et al. [16] Recommender systems can be further classified into memory-based and model-based methods. Memory-based methods store the past behavior of users in memory and use this information to generate recommendations [17]. Model-based methods [18], on the other hand, use statistical models to generate recommendations. Model-based methods can be more scalable and efficient than memory-based methods, but they also require more computational resources.

Limitations of traditional recommender systems are discussed next.

2.4 Limitations of traditional recommender systems

This section presents the limitations observed in existing traditional recommender systems.

Lack of Personalization:

Traditional recommendation systems often rely on broad demographic information [19] or general item features to make recommendations [20]. This can lead to irrelevant or generic recommenda- tions for very large number of users.

Cold Start Problem: Traditional recommendation sys- tems can struggle to make recommendations for new users or items that have little or no information associated with them [21] [22] [23] [24].

Limited Contextual Information: Traditional recom -mendation systems often do not consider the context in which recommendations are being made, which can lead to incorrect or irrelevant recommendations.

Literature related to context based recommender system was surveyed and is discussed in next section.

3. CONTEXT-BASED RECOMMENDER SYSTEMS

By considering the context, context-based recommender systems are able to provide recommendations more accurately to the users which are relevant to them [25].

Several contexts can be used for making recommendations. For example, context can be used to suggest items which are dependent on users current location. such as restaurant or any tourist attraction place present in the vicinity. Time-based context can be used to recommend items that are relevant to the current time of day. Mood based context can be used to suggest products which matches with the current mood of user, such as calming music when the user is stressed. [26]

Context-based recommender systems can also use demographic information, such as users's age, gender, annual or monthly income etc. to provide recommendations that are according to the user's specific needs and behavior. For example, suggesting a comic book or toy for a user of age in range 10-15.

There are three ways to incorporate context in recommender system. [27]

- Contextual pre-filtering
- Contextual post-filtering
- Contextual Modelling

These are discussed in details in next subsections.

3.1 Contextual pre-filtering

In contextual pre-filtering, the most related User*Item data is used for generating recommendations. The contextual information helps us for selecting most usefull rating data , which can be exact or generalized using context. This approach can be used it in combination with any of the possible traditional recommendation methods. Adomavecius et al. [27] suggested a reduction-based approach, which reduces the problem of multidimensional contextual recommendation to the standard 2D User Item recommendation problem [27]. In this approach, contextual information is used to filter or arrange the set of items generated by the underlying recommendation algorithm [28], [29] using the available context information.

3.2 Contextual post-filtering

The contextual post-filtering approach is a recommendation technique that ignores context information while generating recommendations and generates responses according to traditional techniques but minimizes the recommendation output for each user using context information [30]. This is achieved by filtering out irrelevant recommendations. Ranking of recommendations is done based on context-specific item usage patterns. Heuristic and model-based post-filtering approaches are two types of contextual post-filtering techniques. Heuristic technique finds common item attributes for a given user in a given context and then adjusts the recommendations based on these attributes. While model-based method build predictive models to calculate the probability of relevance for specific items in a given context and then adjust recommendations based on this probability. The main benefit of contextual post-filtering is that it can also be used with any of traditional recommendation technique [31].

3.3 Contextual Modelling

Both contextual pre and post filtering uses traditional two-dimensional functions to generate recommendations, While the use of contextual modelling approaches produces multidimensional recommendation functions that may be incorporated into predictive models created using decision trees, regressions, probabilistic models, or other methods. Heuristic-based contextual modeling techniques, such as the nearest neighbor approach, needs to build a contextual profile for every user in a given context, and then finding the N near- est neighbors based on these profiles. Model-based tech- niques, such as the regression-based Hierarchical Bayesian collaborative filtering model, allow for the incorporation of additional contextual attributes, like time and location, into the Hierarchical Bayesian model. Another strategy is the matrix factorization-based strategy, which adds more model parameters to simulate how contextual elements interact with ratings. On the basis of the context modelling paradigm, new techniques have also been created specially for context-aware recommender systems, such as adding contextual aspects right into the recommendation space and utilizing machine learning to generate recommendations [32].

4. APPLICATIONS OF CONTEXT AWARE RECOMMENDER SYSTEMS

Context aware recommendation system for social network have been surveyed by Suhaimet. al. The context information such as user demographics social network structure and location has been used. The features and advantages of these systems include their ability to improve the accuracy and diversity of recommendations, as well as their ability to take into account various types of context information. However, the limitations of these systems include the need for large amounts of data and the difficulty in modeling complex interactions between context and recommendation [33].

A library called DeepCARSKit developed in python has been presented by Zheng et al. It uses deep learning algorithms and provides a common platform for researchers to create, implement, and evaluate various types of context- aware recommendation models. It may be useful for better comparisons and benchmarking. The platform is currently limited to supporting only two types of context-aware recommendation models: FM (factorization machines) and NeuCF (neural collaborative filtering). This limitation may be a drawback for researchers who are interested in exploring other types of context-aware models. Nonetheless, the authors believe that DeepCARSKit represents a significant contribution to the field of context-aware recommendation systems and can serve as a valuable resource for researchers working in this area [34].

The multi-context-aware recommendation system for learning user/item representations using a knowledge graph has been discussed by Wu et al. The propagation-based and path-based approaches and a rule is used to characterize a user's preferences. On the basis of the knowledge network and user behaviours, an rule discovery technique is also put forth that can automatically choose the most representative user preferences templates in a given recommendation situation [35].

In another work, A hybrid algorithm that combines a neural collaborative filtering method and an item-splitting approach for incorporating context [29].

A context-aware recommendation system which uses review mining has been discussed in a work. The system uses a classifier to categorize the user's context from the review texts. The inferred context is then used to produce context-aware recommendations by defining a utility function for items that reflects the user's preferences based on the current context. The system has been tested using a dataset of hotel reviews [36].

An overview of context-aware recommendation systems (CARS) in the IoT environment (IoT-CARS) is discussed. The work defines context as any information that characterizes the situations of users and items in a specific interaction. The goal of CARS was to provide accurate and personalized recommendations by exploiting contextual information. Context-aware recommenders are characterized based on the different IoT contexts and how these contexts are modeled. Challenges faced by CARS, including limitations in learning user profiles and behaviors and the importance of proper context selection in model design also has been discussed[37].

5. CHALLENGES ASSOCIATED WITH CONTEXT BASED RECOMMENDER SYSTEMS

An overview of context-aware recommendation systems (CARS) in the IoT environment (IoT-CARS) is discussed. The work defines context as any information that characterizes the situations of users and items in a specific interaction. The goal of CARS was to provide accurate and personalized recommendations by exploiting contextual information. Context-aware recommenders are characterized based on the different IoT contexts and how these contexts are modeled. Challenges faced by CARS, including limitations in learning user profiles and behaviors and the importance of proper context selection in model design also has been discussed [37].

There are several challenges associated with context-based recommender systems. These challanges are listed below:

• Availability of context data: In order to use context effectively, the recommender system must have access to accurate and relevant context data.

• Integration of context: The recommender system must be able to use context effectively to generate accurate and relevant recommendations. [17]

• Technical challenges: Developing algorithms and models that can effectively incorporate contextual information into recommendation systems is a significant technical challenge. There are several technical issues, such as modeling context, effectively combining different contex- tual factors, dealing with sparsity and cold start problems in the presence of context, and handleing real-time rec- ommendations.

• Evaluation challenges: Evaluating the performance of context-aware recommendation systems is another sig- nificant challenge. There are several evaluation metrics that need to be considered, such as accuracy, diversity, serendipity, novelty, and coverage. The recommendation system's level of performance can also very greatly depend on the evaluation measures chosen. Addition- ally, there are no standardized evaluation methods and datasets to analyze output of recommendation systems. This makes it difficult to compare the performance of different context-aware recommendation systems.

• User-related challenges: One significant challenge is ensuring user privacy and data protection while collecting and using contextual information. Challenge is under- standing user preferences and behavior in the presence of context, and designing recommendation systems that can effectively adapt to changing user preferences over time. Additionally, user acceptance and trust in the recommen- dation system can be a challenge, as some users may find contextual recommendations intrusive or annoying.

6. CONCLUSION

In this paper, we conducted an exhaustive study on context-based recommender systems. We reviewed a wide range of approaches and techniques used in this domain and discussed their strengths and weaknesses. Through our analysis, we identified several key trends and challenges in the field, including the need for effective context representation, the importance of user feedback, and the trade-off between accuracy and diversity in recommendations. We can conclude that context- based recommender systems have enormous potential to improve user satisfaction and engagement in various domains such as e-commerce, entertainment, and education. Overall, our study highlights the importance of ongoing research and development in the field of context-based recommenders. We hope that this survey paper will serve as a valuable resource for researchers and practitioners alike, and inspire new ideas and approaches to enhance the performance and usability of these systems.

7. REFERENCES

[1] Y. Koren, S. Rendle, and R. Bell, Advances in Collaborative Filtering. New York, NY: Springer US, 2022, pp. 91–142. [Online]. Available: https://doi.org/10.1007/978-1-0716-2197-43 .

[2] J. Basilico and T. Hofmann, “Unifying collaborative and content-based filtering,” in Proceedings of the Twenty-First International Conference on Machine Learning, ser. ICML ’04. New York, NY, USA: Association for Computing Machinery, 2004, p. 9. [Online]. Available: https://doi.org/10.1145/1015330.1015394

[3] G. Geetha, M. Safa, C. Fancy, and D. Saranya, “A hybrid approach using collaborative filtering and content based filtering for recommender system,” Journal of Physics: Conference Series, vol. 1000, no. 1, p. 012101, apr 2018. [Online]. Available: https://dx.doi.org/10.1088/1742-6596/1000/1/012101.

[4] B. Alhijawi and Y. Kilani, “The recommender system: a survey,” International Journal of Advanced Intelligence Paradigms, vol. 15, no. 3, pp. 229–251, 2020. [Online]. Available: https://www.inderscienceonline.com/doi/abs/10.1504/IJAIP.2020.105815

[5] K. Haruna, M. Akmar Ismail, S. Suhendroyono, D. Damiasih, A. C. Pierewan, H. Chiroma, and T. Herawan, “Context-aware recommender system: A review of recent developmental process and future research direction,” Applied Sciences, vol. 7, no. 12, 2017. [Online]. Available: https://www.mdpi.com/2076-3417/7/12/1211

[6] . Milano, M. Taddeo, and L. Floridi, “Recommender systems and their ethical challenges,” AI & SOCIETY, vol. 35, no. 4, pp. 957–967, 2020. [Online]. Available: https://doi.org/10.1007/s00146-020-00950-y

[7] J. Lu, D. Wu, M. Mao, W. Wang, and G. Zhang, “Recommender system application developments: A survey,” Decision Support Systems, vol. 74, pp. 12–32, 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167923615000627

[8] S. Reddy, S. Nalluri, S. Kunisetti, S. Ashok, and B. Venkatesh, “Content-based movie recommendation system using genre correlation,” in Smart Intelligent Computing and Applications, S. C. Satapathy, V. Bhateja, and S. Das, Eds. Singapore: Springer Singapore, 2019, pp. 391–397.

[9] P. M. Alamdari, N. J. Navimipour, M. Hosseinzadeh, A. A. Safaei, and A. Darwesh, “A systematic study on the recommender systems in the e- commerce,” IEEE Access, vol. 8, pp. 115 694–115 716, 2020.

[10] W. Fan, Y. Ma, Q. Li, Y. He, E. Zhao, J. Tang, and D. Yin, “Graph neural networks for social recommendation,” in The World Wide Web Conference, ser. WWW ’19. New York, NY, USA: Association for Computing Machinery, 2019, p. 417–426. [Online]. Available: https://doi.org/10.1145/3308558.3313488

[11] D. Paul and S. Kundu, “A survey of music recommendation systems with a proposed music recommendation system,” in Emerging Technology in Modelling and Graphics, J. K. Mandal and D. Bhattacharya, Eds. Singapore: Springer Singapore, 2020, pp. 279–285.

[12] . Schedl, “Deep learning in music recommendation systems,” Frontiers in Applied Mathematics and Statistics, vol. 5, p. 44, 08 2019.

[13] H. Han, C. Wang, Y. Zhao, M. Shu, W. Wang, and Y. Min, “Ssle: A framework for evaluating the “filter bubble” effect on the news aggregator and recommenders,” World Wide Web, vol. 25, no. 3, pp. 1169–1195, May 2022. [Online]. Available: https://doi.org/10.1007/s11280-022-01031-4

[14] B. Walek and V. Fojtik, “A hybrid recommender system for recommending relevant movies using an expert system,” Expert Systems with Applications, vol. 158, p. 113452, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417420302761

[15] P. Kouki, J. Schaffer, J. Pujara, J. O’Donovan, and L. Getoor, “Personalized explanations for hybrid recommender systems,” in Proceedings of the 24th International Conference on Intelligent User Interfaces, ser. IUI ’19. New York, NY, USA: Association for Computing Machinery, 2019, p. 379–390. [Online]. Available: https://doi.org/10.1145/3301275.3302306

[16] P. H. Aditya, I. Budi, and Q. Munajat, “A comparative analysis of memory- based and model-based collaborative filtering on the implementation of recommender system for e-commerce in indonesia: A case study pt x,” in 2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS), 2016, pp. 303–308.

[17] F. Ricci, L. Rokach, and B. Shapira, Recommender Systems: Introduction and Challenges. Boston, MA: Springer US, 2015, pp. 1–34. [Online]. Available: https://doi.org/10.1007/978-1-4899-7637-61

[18] S. Zhang, L. Yao, A. Sun, and Y. Tay, “Deep learning based recommender system: A survey and new perspectives,” ACM Comput. Surv., vol. 52, no. 1, feb 2019. [Online]. Available: https://doi.org/10.1145/3285029

[19] M. H. Mohamed, M. H. Khafagy, and M. H. Ibrahim, “Recommender systems challenges and solutions survey,” in 2019 International Conference on Innovative Trends in Computer Engineering (ITCE), 2019, pp. 149–155.

[20] S. Kulkarni and S. F. Rodd, “Context aware recommendation systems: A review of the state of the art techniques,” Computer Science Review, vol. 37, p. 100255, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1574013719301406

[21] S. Natarajan, S. Vairavasundaram, S. Natarajan, and A. H. Gandomi, “Resolving data sparsity and cold start problem in collaborative filtering recommender system using linked open data,” Expert Systems with Applications, vol. 149, p. 113248, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417420300737

[22] J. Herce-Zelaya, C. Porcel, J. Bernab´e-Moreno, A.

Tejeda- Lorente, and E. Herrera-Viedma, “New technique to alleviate the cold start problem in recommender systems using information from social media and random decision forests,” Information Sciences, vol. 536, pp. 156–170, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0020025520304916

[23] W. Fu, Z. Peng, S. Wang, Y. Xu, and J. Li, “Deeply fusing reviews and contents for cold start users in cross-domain recommendation systems,” Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, no. 01, pp. 94–101, Jul. 2019. [Online]. Available: https://ojs.aaai.org/index.php/AAAI/article/view/3773

[24] B. Lika, K. Kolomvatsos, and S. Hadjiefthymiades, “Facing the cold start problem in recommender systems,” Expert Systems with Applications, vol. 41, no. 4, Part 2, pp. 2065–2073, 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417413007240

[25] S. Raza and C. Ding, “Progress in context-aware recommender systems :an overview,” Comput. Sci. Rev., vol. 31, no. C, p. 84–97, feb 2019. [Online]. Available: https://doi.org/10.1016/j.cosrev.2019.01.001

[26] K. Verbert, N. Manouselis, X. Ochoa, M. Wolpers, H. Drachsler, I. Bosnic, and E. Duval, “Context-aware recommender systems for learning: A survey and future challenges,” IEEE Transactions on Learning Technologies, vol. 5, no. 4, pp. 318–335, 2012.

[27] G. Adomavicius, B. Mobasher, F. Ricci, and A. Tuzhilin, “Context-aware recommender systems,” AI Magazine, vol. 32, pp. 67–80, 09 2011.

[28] F. Ricci, L. Rokach, and B. Shapira, Eds., Recommender Systems Handbook. Springer US, 2015. [Online]. Available: https://doi.org/10.1007/978-1-4899- 7637-6

[29] I. M. A. Jawarneh, P. Bellavista, A. Corradi, L. Foschini, R. Montanari, J. Berrocal, and J. M. Murillo, “A pre-filtering approach for incorporating contextual information into deep learning based recommender systems,” IEEE Access, vol. 8, pp. 40 485–40 498, 2020.

[30] Z. El Yebdri, S. M. Benslimane, F. Lahfa, M. Barhamgi, and D. Benslimane, “Context-aware recommender system using trust network,” Computing, vol. 103, no. 9, pp. 1919–1937, 2021. [Online]. Available: https://doi.org/10.1007/s00607-020-00876-9

[31] Y. Zheng, “Context-aware mobile recommendation by a novel post-filtering approach,” 06 2018.

[32] F. Lahlou, H. Benbrahim, and I. Kassou, “Context aware recommender system algorithms : State of the art and focus on factorization based methods,” Electronic Journal of Information Technology, 11 2017.

[33] A. B. Suhaim and J. Berri, “Context-aware recommender systems for social networks: Review, challenges and opportunities,” IEEE Access, vol. 9, pp. 57 440–57 463, 2021.

[34] Y. Zheng, “Deepcarskit: A deep learning based context-aware recommendation library,” Software Impacts, vol. 13, p. 100292, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2665963822000380

[35] C. Wu, S. Liu, Z. Zeng, M. Chen, A. Alhudhaif, X. Tang, F. Alenezi, N. Alnaim, and X. Peng, “Knowledge graph-based multi-context-aware recommendation algorithm,” Information Sciences, vol. 595, pp. 179–194, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0020025522001967

[36] N. Hariri, B. Mobasher, R. Burke, and Y. Zheng, “Context-aware recommen- dation based on review mining,” 07 2011.

[37] D. Nawara and R. Kashef, “Context-aware recommendation systems in the iot environment (iot-cars)–a comprehensive overview,” IEEE Access, vol. 9, pp. 144 270–144 284, 2021.