Mapana – Journal of Sciences
2022, Vol. 21, No. 1, 73-92
ISSN 0975-3303/https://doi.org/10.12723/mjs.60.6

Recommender System (RS): Challenges, Issues & Extensions

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Abstract

Recommendations are long chains followed from traditional life to today's life. In everyday life, the chain of recommendation augments the social process via some physical media and digital applications. The issues and challenges of recommendation are still in the infancy due to the growth of technology. This article identifies the uncovered areas of concern and links them to novel solutions. We also provide an extensive literature with different dimension for the newbie to work with the subject. We observed the study with different taxonomy provided by the prevalent researcher of the recommender system. This article gives the remedial solution of the recommendation problems

Keywords: Algorithms, Artificial Intelligence, Digital Challenges, Machine Learning, Recommender Systems, Deep Learning

1. Introduction

Recommender systems are the software algorithms which are widely used in digital systems to assist people. The journey of the recommender system is very long from the Tapestry to the modern world (Goldberg et al., 1992) [2]. On an individual stop of the journey, some improvements have been made from ethical challenges to real time problems of the recommender system. The recommendations explicitly collaborate with the nuances of the digital world. The recommendations are generally the inputs of

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individual or some specific groups which in turns the recommender aggregates and returns to the known recipient of the system (Paul et al., 1997) [1]. The recommendations suggested to the known recipient may be particularly interesting items, which are the aggregate evaluations of the recommender system to indicate those that should be filtered out. The various filtering convenient to put in the recommender system are such as "content-based filtering", "collaborative filtering" etc. The phrase "collaborative filtering" suggested by the developer of first recommender system i.e., Tapestry (Goldberg et al., 1992) [2] that to handle the large volume of email documents and map the set of documents of interest to a known recipient. With the evolution of collaborative filtering the different versions of recommendations are presented in a few years i.e., used based, content based and hybrid model of recommendation.

Modern era is revolving around more personalized recommendations to earlier recommendations. In the 90's from the evolution of collaborative filtering in the recommendation the chief focus was on developing the recommender system mostly for business application to boost the revenue of the implemented model. Also, facts prove this phrase that as follows:

Two thirds of movie watched by Netflix customers are recommended movies 38% of click-through rates on Google news are recommended links 35 % of sales at Amazon arise from recommended products. Choice stream claims that 28% of people would like to buy more music, if they find what they like.

RS are ubiquitous and there is enough research present to direct the researcher or developers to know the development of efficient RS systems further. Also, in the last 20 years the several systematic literature reviews present various taxonomy of research problems in recommendation systems [4]. On the other side the concern of privacy and security became a hurdle to the providers of recommendation systems to bite the information that could comprise their user's information (Chen et al., 2009) [5].

2. Recommender System

In today's world the recommendation is the need of social as well as personal life. The modern world of recommendation process is forwarding toward the much-personalized recommendation with the evolution of relative newness in the technology. With the advancement of technology like deep neural network, artificial intelligence, the recommendation problems of finding good items could be achieved with the help of implicit feedback, or using a multi-criteria recommender system. However, the research questions of the recommender system are still in infancy.

RQ1: what the space option is present to match the taste of known to unknown user or item;

RQ2: Content of evaluation (Either Implicit or Explicit), Recommendation May be (anonymous, tagged with source identity or tagged with pseudonym);

RQ3: Factors evolved in performance evaluation of good recommendation;

Various researchers present the distinct level of abstraction taxonomy to address the recommendation problem (Batmaz et al., 2019) [45,46 & 47]. In the business model the space of options may be the individual unrated item, taxonomy item or grouped item, recommended item by the other group which turns in a purchase. For the evaluation of recommendation, one may use multiple criteria to match with actual behavior after recommendation is fed. In the domain of music, email, news several recommendation systems are available Ringo's, Tapestry and News Net respectively with their limitation and filtering technique. Click through rates as a proxy is a good way to evaluate the accuracy of the system recommendation for the news items. The technical prospect on the recommendation process is very wide. However, our concern is sparked by identifying the extension of existing literature and their challenges in the system. Further the scope of research in the field of machine learning algorithms, deep learning enable recommender systems are much wider.

Dynamic Recommender System Model

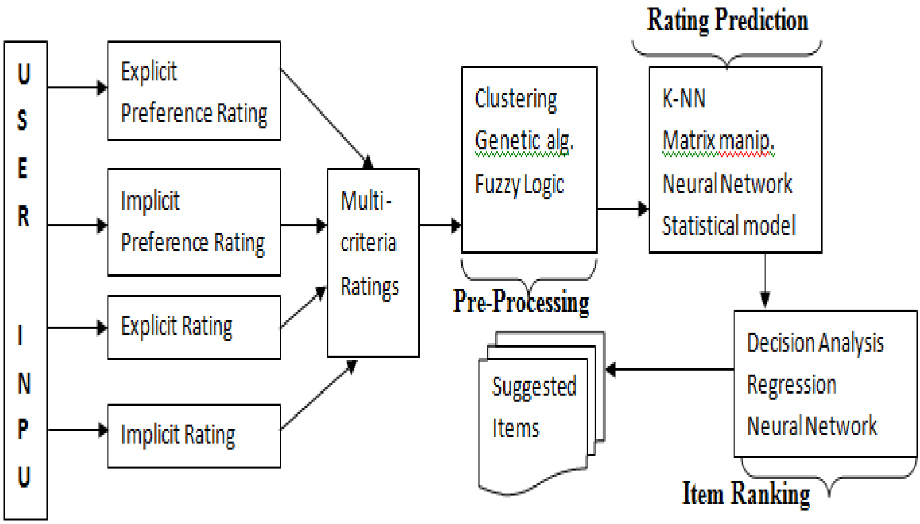

Fig. 1: Recommendation system model [9]

A dynamic recommender system model is considered to map the challenges faced in the design and implementation of recommender system. The analysis of study may now categorize the issues cause by recommender systems in distinct dimensions.

1) How much a false recommendation impacts the utility of system?

2) Whether the false recommendation impact constitutes an immediate harm or the long-term impact will be there in recommendation to a particular item.

With the help of RS research question, we are now ready to review the contributions given in current literature.

3. Literature

Sr. No	Author	Proposed Work / Extension	Application/ Dataset
1	Paul Resnic [1] et al., 1997	Give a thought to implementation of business models with recommender systems to generate the good revenue for the maintenance of recommender systems. Moreover, suggested four models based on the taste of users to recommend the items and generate revenue to sustain in the world.	Group Lens Fab Referral Web PHOAKS Siteseer
2	David Goldberg [2] et al., 1992	Developer of the first recommender system is Tapestry who first uses collaborative filtering with Tapestry. Annotations are good for recommendation but the taste of the user changes every second so, it limits the system to recommend the items based on annotations only. Another concern is the security and design of the appraiser which can be extended to do the good recommendation of documents to the user.	General Net News
3	Charu C. Aggarwal [3] et al., 1999	Rating based collaborative filtering, horting and predictability as the new twin parameters suggested in the work. The approach used is based on directed graphs which are collections of edges and vertices. The ratings are stored with the edges for items rated by the user. The complexity of the system is increased due to storing the directed graph.	Like minds Firefly

4	Upendra Shardanand [6] et al., 1995	The system Ringo is developed with the help of content-based filtering to recommend music to the users based on the user profiles. The two algorithms suggested by the author Constrained person r Algorithm and artists artist algorithm shows a good accuracy with the given data set of RINGO. Moreover, the author is silent about the clustering used in the system to compute similarity measure.	General Ringo
5	Nathan N. Liul [7] et al., 2010	Presented more complex models for the temporal dynamics of user feedback by incorporating more advanced time series analysis and modeling technique	General Group Lens Movie Lens
6	Mohammad [8] et al., 2010	A similar approach can be applied to items. A recent research topic where it can be extended is recommendation to groups	General Group lens Movie Lens
7	Karatzoglou [9] et al., 2010	Further investigating the use of model to further explore temporal dependencies in standard CF settings while also dealing with implicit feedback. We can also plan on exploring how multidimensional TF can be used to model non contextual variable such as those related to content and user.	General Netflix /Yahoo
8	Robin [10] et al., 2010	Further many collaborative recommendations, while some have been extensively evaluated statically; their dynamic properties are largely unknown.	General Group lens Movie Lens

9	Adomavicius G [11] et al., 2005	In this article Online collaborative filtering methods that can incorporate new data in real time are advantageous in many practical situations. However, this problem has not been adequately addressed. Training was comparatively slow, but still manageable, and could be improved by a straightforward parallelization.	General Group lens Movie Lens
10	Pessemier [12] et al., 2010	In further research, we can verify our conclusion with other data sets and an online evaluation. Moreover, we will try to generalize the conclusion for more types of recommendation algorithms. Finally, we will investigate the optimal time period to log the consumption data for recommendation purpose.	General Group lens Movie Lens
11	Karagiannidis [13] et al., 2010	More experiment to show the increase of accuracy by the current VF methodology and further expand hydra with the addition of more modules for preprocessing of datasets, insertion of more algorithms into hydra's algorithms pool, creation of more VF policies and experimentation on other datasets to find the most critical data field and most effective algorithm for each application.	General Group lens Movie Lens
12	Woerndl [14] et al., 2007	In ongoing work, we intend to explore different fields of context-awareness, among other the effect of the cost of items on context, implicit context identification, and context-aware evaluation.	General Group lens Movie Lens TV

13	Lu [15] et al., 2009	Our Future work will focus on better models for joint and dynamical estimation of user factors and item factors, including bilinear filtering model based on Sigma-point kalman filter, and parameterized regression models as in.	General Group lens Movie Lens Yahoo
14	Park [16] et al., 2009	As for future work, extensively compare with other existing variants along the direction of feature-based modeling on ranking quality in cold-start situations.	General Group lens Movie Lens
15	Gunawardana [17] et al., 2009	Our models do not explicitly take temporal effects into account, even though these effects can be important in some domains. Extending our models to take such effects into account is left for future work.	General Group lens Movie Lens Shopping
16	Hurley [18] et al., 2011	In the next stage we can put more diversity problems from the system perspective (Long Tail Problem). More efficient algorithms need to be developed.	General Group lens Movie Lens
17	Carlos [19] et al., 2009	In future work we can explore the effectiveness of a much broader set of recommendation algorithms for use in online forums. Hence enhancement to standard KNN.	Student, Second Life, Railway.
18	Chen [20] et al., 2009	RS is evaluated based on the PC dataset. A user study will be carefully designed and performed to justify the simulation studies in the next step.	PC data sets
19	Baltrunas [21] et al., 2009	The method proposed here can be generalized in several ways. Split the users(not the items)according to the context, or one can mix these two approaches or search a better criteria for splitting	Yahoo, Web scope

20	Kawamae [22] et al., 2009	More datasets to show that temporal precedence in user behavior is useful for recommending items that match the latest user preferences.	General Netflix
21	Abbassi [23] et al., 2009	Despite being a recognized problem, over-specialization is addressed in an ad-hoc manner. More research is needed in this direction.	General Group lens Movie Lens
22	Marius [24] et al., 2009	In Future work we can deal with some technical limitations of the current approach and we will perform new user studies with a larger users population	Music
23	Nkechi [25] et al., 2009	This work provides a greater insight into the effects of context on recommender systems	General
24	Asela [26] et al., 2008	It proposes three directions for extending the ideas present in this paper Extending BM	General Group lens Movie Lens
25	Haoyuan [27] et al., 2008	In future we can apply PFP on the query logs to support related search for Google Search Engine	General Dataset
26	Greg Linden [28] et al., 2003	In this industry report the item-to-item collaborative filtering is recommended over the traditional collaborative filtering for the large population or where the customer data sets and product catalog are very large. In future the retail industry or e-commerce application can use item to item collaborative filtering for target marketing, both online and offline.	General Amazon
27	Mi Zhang [29] et al., 2008	In future work we can apply the methodology presented here to other problems in information retrieval. We can also consider other methods for enabling novel but relevant recommendations.	General Group Lens Movie lens

28	Young [30] et al., 2008	In particular, the focus is on the challenge of selecting the training data for unknown rating predictions that can be solved to some extent by rating variance.	General Group Lens Movie lens
29	Erich [31] et al., 2008	It presents a high-level view of an extended recommender architecture which accounts both for the incorporation of psychological phenomenon as well as for the debugging of MAUT bases	General
30	Sara Drenneret [32] al., 2008	In this we would like to expand our focus beyond the entry process, seeking to shape user behavior throughout the user lifecycle by suggesting tasks for users to perform. Also we would like to develop a unified metric for quantifying different types of user contribution to an online community	General
31	Neal Lathia [33] et al., 2008	The evolution of similarity between any pair of users is dominated by the method that is used to measure similarity, these kinds of insights offer the potential to improve KNN algorithm in a number of ways	General Group Lens Movie lens
32	Nima [34] et al., 2007	Take into account evidence from other source of information, such as web content and structure	Web traffic simulator
33	Tavi [35] et al., 2007	We are seeking a more robust method for determining similarity between items when data is very sparse. Doing so would introduce more diversity among recommendations and may further reduce portfolio effects	General Jester

34	Jiyong Zhang [36] et al., 2007	Soundness of the proposed algorithm on a larger dataset and make it more efficient. We can also plan to apply an algorithm to the item-based CF approach to test its performance	General Group Lens Movie lens
35	Vinod [37] et al., 2008	Indeed, comparing recommendations are more complex since there are no standard metrics to compare recommendations from two sources. Some recent and widely accepted metrics include trust, diversity, and serendipity.	General Group Lens Movie lens
36	Silvia Milano [38] et al., 2020	Discuss the different level of abstraction by the literature and corresponding performance of recommender systems in areas of concern like inappropriate content, privacy, opacity etc. in future the implementation can be extended to both sides of recommendations i.e. at receiver, stakeholder and feedback can be attached with evaluation.	General
37	Diego Monti [39] et al., 2020	In this the ninety-three studies are considered to identify the growth of multi criteria RS in a different era and answer the research question in the multi criteria-recommendation.	General Yahoo movie Trip-advisor In-House Movie-lens Synthetic
38	Markus [40] et al., 2007	A recommender system with a commercial context is used to test the recommender system in context of an actual world data-store named fine cigar.	Fine Cigar
39	Paul [41] et al., 1994	A platform to recommend the news articles according to the ratings given by explicit users from a huge stream of articles.	Netnews

40	Gediminas [42] et al., 2005	Discuss the several extensions possible in the new generation towards the recommendation methods and the state of art for the personalized RS, hybrid RS with distinct techniques.	General
41	Linyuan Lü [43] et. al., 2012	Discuss the issues and challenges like accuracy, sparsity, and cold start problem of RS with different approaches of design and implementation using machine learning, deep learning.	Netflix
42	Batmaz [44] et al., 2019	Presents the literature on deep learning algorithms using a RS by focusing on three major parameters i.e. accuracy of predicted rating, sparsity with different CF algorithms	
43	F. Mansur [48] et al., 2017	The suggested shortcoming of recommender system through a survey is presented with the working of the popular technique used in recommender system.	General
44	Asemi A [49] et al., 2022	Presents the integrated model to test the big data application and design issues in the recommendation system. Ontology driven recommendations are suggested in article.	Bigdata, ontology
45	Tugba [50] et al., 2022	Proposed the novel top-n recommendation based on neighborhood similarity of multi criteria predication of items.	General
46	Sinha [51] et al., 2022	This article presents the study of 125 literatures prevalent in the domain of recommendation research.	General
47	Nguyen [52] et al., 2022	Discuss the latent factor model as a state of art in the subject of RS. The present study achieves good accuracy in recommendation of items using LF model.	General

48	N. Yi [53] et al., 2017	Proposed a novel implementation of movie recommender system coincides with traditional CF using a graph database.	Graph Database Matrix
49	Gupta [54] et al., 2020	A movie recommender system is studied using apache mahout machine learning-based technology to suggest movie recommendations.	Movie lens
50	Son [55] et al., 2014	Presents the distinct solution available to work with cold start problem of recommender system.	General

4. Discussion

Based on the literature presented several researchers have found numerous recommendation problems of research. Some of them are fragmented into taxonomy that we display above. Starting from a space of option, the challenge coincides with information security target to individual user's rights violations. Several recommendation engines targeted to violate the privacy concern for recommending items such that the user personal autonomy and identity reviled unfairness type of immediate harm to the violation of the right. Moreover, the evaluation content plays a significant role in the recommendation system's future research. The evaluation criteria to measure the performance of recommendations are a big challenge in the study. On the other hand, the uncovered challenges of RS like sparsity, cold start problem, accuracy, and scalability are still a future research challenge for newbies in the recommender system. Some prevalent technologies like deep learning, restricted Boltzmann machines, deep belief networks, and auto encoders show the domain's good respone. A deep learning-based recommender system reflects an increasing graph of accuracy for recommendations and improves the other issues of RS.

5. Conclusion

The article presents a link between the challenges, issues and possible extension of literature with their application domain. It also sparks the gap in the studies given in last twenty years. The recommendation with relative newness in technology gives a big jump to challenges and extension for the next generation of recommendations. The recommendation challenges in artificial environment associated deep learning and neural network technology makes the state of the art. In future, personalized recommendation could become the challenging state of art for the recommendation researchers.

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