Temporal Recommendation Systems: A Review

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Abstract: *Recommendation Systems have gained a wider attention due to large amount of generated data in digital world. The more are the services provided to the users, more are the users in dilemma in choice of the appropriate services. In this situation, recommendation systems play an important role as they suggest services based on user's interests. This eases the task of user and improves the decision making. Though traditional recommendation systems have succeeded successfully in generation of accurate suggestions but it has been observed that users' interests changes with time. This issue has prompted the researchers to work towards the direction of temporal recommendation systems. This research study provides the systematic review of temporal recommendation systems including the benefits and challenges faced in this domain. This study would benefit the researchers working in this domain and also e-commerce sectors towards the growth of business.*

Keywords: drift, dynamic, interests, recommendations, temporal models

I. INTRODUCTION

Recommendation Systems are the information filtering systems that recommends the items based on the users interests within a short span of time. Though traditional recommendation systems generate accurate suggestions and have attained good results. It has been successfully applied to various domains like recommendation of products, videos, friends, blogs, jobs, books, movies, and many more [7]. It not only suggests items based on user's interests but also users get an opportunity to explore a variety of new items.

Traditional Recommendation systems have been broadly categorized into three categories: Content-based, Collaborative Filtering and Hybrid-based recommendation systems [11]. Firstly, content-based recommendation systems suggest the similar items based on the feature of items, profile of users, past purchase history. There are various measures to compute the similarity of items like dot product, cosine similarity and many more. For instance, suppose user has watched movie of action genre, then system would suggest similar movies based on action genre. The major advantage of content based filtering systems are that these are not dependent on the other users as recommendations are done based on the own profile of users.

In fact, those items are also suggested that might not be liked by other users. The major limitations of content-based recommendations systems are that suggestions are generated only based on the existing interests of users and it is difficult to suggest some items apart from their interests. Moreover, proper domain knowledge is required to represent the feature of items. Secondly, collaborative filtering-based recommendation systems suggest items on the basis of similar users' interests [9]. For instance, if user

1 has liked movies M1, M2, M3 and M4 and user 2 has liked movies M2, M3, M4, then this indicates that user 1 and user 2 are similar. It is more likely that user 2 would also like movie M1 as both users share common interests. There are various measures to compute the similarity of users like Pearson Correlation Coefficient and many more [6]. The major advantages of collaborative filtering systems are that no domain knowledge is required as items are recommended based on the similarity of users. Moreover, in contrast to content based recommendation systems, in this technique, users get suggestions based on the taste of other similar users, hence got a chance to explore new items which might not be thought off at own level. The major limitations of collaborative-filtering systems are its difficult to suggest the items those are new to the system known as cold-start problem. In addition to this, it is difficult to incorporate the contextual features of items. Thirdly, hybrid recommendation systems are the combination of different recommendation systems to gain advantages of one over the other and improve the performance [8]. There are different types of hybrid recommendation systems such as weighted hybrid recommendation system, feature combination, cascade, feature augmentation, meta- level, switching and mixed recommendation systems. Thus, in contrast to content-based and collaborative-filtering based recommendation systems, hybrid recommendation systems can be the better solution in certain situations [10].

It is observed from the different types of traditional recommendation systems that mainly recommendations are done on the basis of ratings factor. However, users' interests are dynamic in nature that is changes with time. For instance, it can be the scenario that user likes action movies in year 2015, thriller movies in 2018 and then romantic movies in 2020. Now, if the system suggests action movies to the user in 2020, then those suggestions might be inappropriate for the user at that specific point of time. Thus, it has become important to incorporate the side features like time is one of the crucial factors that can be included and might affect the performance of recommendation systems [3]. This has evolved the concept of temporal recommendation systems. The large amount of work has been accomplished in this direction; hence this study provides a comprehensive review that would help the researchers and academicians working in this domain.

The paper is organized as: Section II describes the relevant work done in this domain; section III discusses the benefits, section IV details the challenges confronted and section V concludes the current research study.

II. THEORETICAL BACKGROUND

The researchers have successfully designed various algorithms and striving towards better results; thus, this is an active area of research. The Figure 1 below shows the generalized workflow of temporal recommendation systems.

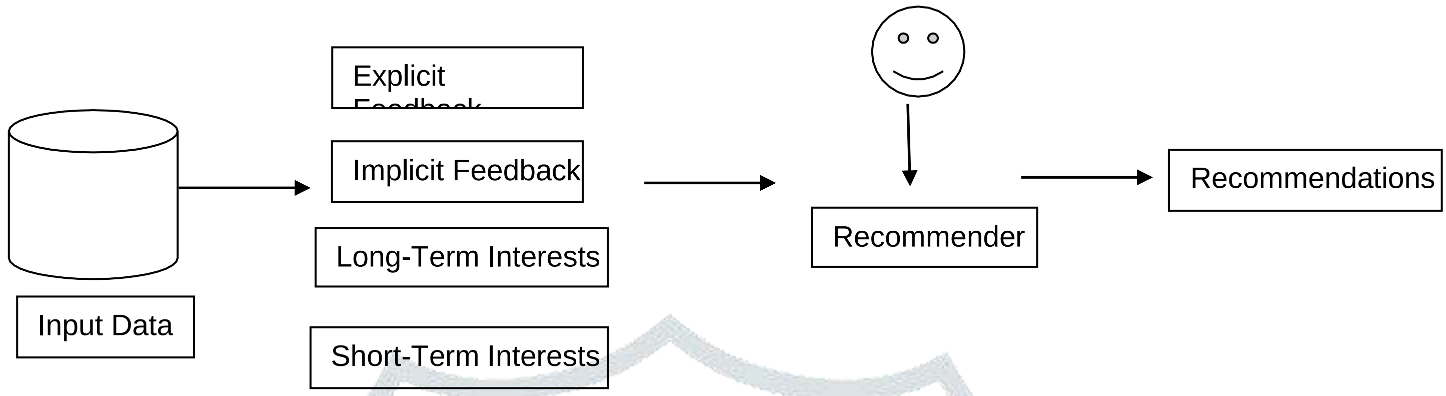

Figure 1. Temporal Recommendation Systems Workflow

The Figure 1 above shows that data is given as an input to the model. The users' interests are captured in either of the forms like explicit feedback in the form of ratings, implicit feedback and along with these interests are captured over a period of time. The integration of short- term and long-term interests can improve the recommendations quality as user's interests are dynamic in nature. This sub-section describes the most prominent work accomplished in this domain.

In 2009, researchers [5] conclude that inclusion of temporal dynamics in both factorization and neighbourhood models improves the quality of recommendations. In 2010, authors proposed a novel recommendation algorithm that integrates short-term and long-term preferences as user preferences changes with time [1]. The findings conclude significant improvements over existing methods. In 2013, researchers [2] did a detailed study and observed that it's become difficult for users to browse books in library, thus in such situations recommendation systems play an important role. The findings conclude that if less weightage is given to old ratings, then rating prediction quality can be improved further. In 2016, authors [4] proposed a point-of-interest recommendation system taking into consideration temporal dynamics as users' preferences to visit places might be different for week-days and weekends. The results justify that the proposed method outperforms the existing methods.

III. BENEFITS OF TEMPORAL RECOMMENDATION SYSTEMS

The inclusion of time dimension in addition to other features would improve the accuracy of recommendation systems. The time dimension can be used differently in different contexts like exact time can be noted at which user is interacting with the system or time can be categorized into different periods of interest. This sub-section details the advantages of inclusion of time dimension into traditional recommendation systems [5]:

a) The user has varying interests in different periods of time and same user expects from the system. For instance, on weekdays, user is interested in reading action novels and, on weekends, user is interested in comedy novels. Thus, based on different category of time domains suggestions should be generated to the users.

b) The inclusion of time domain would filter out the irrelevant suggestions based on the selection of time. For instance, user has selected time at 11:00 p.m. to visit for dinner, and then all the restaurants that are closed at that time would be filtered out.

c) The incorporation of time factor would improve the recommendation quality as recommendations would be generated on recent interests. For instance, user liked the action novels since last few years, but now the recent likings are towards literature novels. Thus, a system would capture the recent interests from user's profile and in accordance the recommendations would be generated.

d) The time dimension can be utilized in the form of time-spent on a particular web page of a website. The amount of time spent can be utilized as a good indicator to know the likings/disliking of the users.

e) The time factor can be used in the form of sequence that would improve accuracy of recommendations. For instance, a user has started watching web series of a particular star cast, and then more is the probability of recommending the similar web series in sequence of same cast.

f) The inclusion of time dimension would recommend more novel items as per user's interests. The time factor can be utilized to filter out the suggestions of old items as these might not be beneficial for the users at that specific point of time.

IV. CHALLENGES OF TEMPORAL RECOMMENDATION SYSTEMS

Temporal recommendation systems have improved the recommendation quality to the greater extent. The periodic interests of the users are broadly captured in the form of short-term interests, long-term interests and integration of both types of interests. It is a challenging task to recommend the items peculiar to users' interests in accordance with the time [3]. The drifting interests of users with time can affect the recommendation quality that might be due to change in mood or popularity of other items can influence the user's decision. For instance, user might be interested in watching action movie at that specific point of time but as per profile the long term interests are of watching comedy genre movies. Similarly, the trends or popularity of other items can also influence the decision. Thus, these factors have to be properly taken into consideration during the design of temporal recommendation systems. The integration of short-term and long-term preferences helps in attainment of good recommendations.

V. CONCLUSION

The increase of information on the web has increased the demand of recommendation systems in different domains. The current research study details the different traditional recommendation systems along with their advantages and disadvantages. However, nowadays the users' interests' changes with time, this has made the concept of temporal recommendation systems more popular. This research paper provides a comprehensive review detailing about the importance of temporal recommendation systems. The prominent work accomplished in this domain has also been outlined. This research study lists the benefits of inclusion of time dimension in the traditional recommendation systems along with the challenges confronted in this domain. This study would be beneficial for the researchers and academicians working in this domain as it highlights the importance of inclusion of time factor along with other features.

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