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Beyond Matrix Completion of the traditional Recommender System

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***Abstract*: The main goal of recommender systems is to predict unknown ratings of items for users. This can be seen as the task to complete the user-item matrix. Method such as matrix factorization can solve this task and have been successfully applied in various domains. However, for some scenarios these general approaches work not as well. So there is a need of some mechanism which can use user-item information and user ratings instead of classical two dimensional matrix recommender systems. In this paper, we have incorporated user-item background information using fuzzy logic in such a way that it improves the performance of traditional recommender systems.**

INTRODUCTION

In the age of information overload on the web, users employ many techniques to take decisions about how to utilize their free time, what to purchase, and even whom to date. Recommender system (RS) automates some of these techniques to provide effective recommendations to users while interacting with large information spaces. RS recommends everything from movies, news, books, songs and Web sites to more complex suggestions for electronic gadgets, matrimonial matches, financial services, etc [1]. In mid-90s, researchers started working on the development of recommendation algorithms by retaining a variety of filtering techniques namely collaborative filtering and content based filtering2. During the last decade, a lot of research has been carried out in the field of RS to design new algorithms for enhancing the recommendation accuracy.

Generally traditional RS generates suggestions to users through four filtering techniques content based filtering (CBF), collaborative filtering (CF), demographic filtering (DMF) and hybrid filtering techniques [2]. CBF recommends items similar to those the user preferred in the past while DMF utilizes user attributes, classified as demographic data, for generating recommendations. Among these techniques, collaborative filtering (CF) has been established as the most successful and widely implemented technique in the area of RS. This interest produced a number of RS for various domains, such as Ringo for music, the BellCore Video Recommender for movies, and Jester for jokes. The basic idea of CF algorithm is to capture a user's preferences for building a user profile and then search for similar ones. These profiles are used to generate new suggestions to users. CF algorithm is broadly classified into memory-based and model-based systems9. Memory based systems are more accurate but they suffer from scalability problem whereas model based approaches are more scalable but less accurate. Al-Shamri and Kamal [3] developed a model that retains the accuracy of memory based CF and scalability of model based CF.

Items

Users	*1*	*2*	...	*i*	...	*m*
1	5	3		1	2	
2		2				4
:			5			
u	3	4		2	1	
:					4	
n			3	2		

Figure 1: Traditional user-item rating matrix

Besides benefits of CF technique, it suffers from many other problems like data sparsity and cold start problems. Basically, CF depends on the user and item ratings while computing the similarity among the users. Computing similarity efficiently is a major concern in the area of RS. In such case, considering additional information apart from external ratings into similarity computation step can resolve sparsity issue. In literature, contextual ratings have proved to be valuable information for providing more accurate recommendations by improving the effectiveness of RS [4]. For example, a user may like to watch a comedy movie at home with family and action movie at a cinema with friends. This example illustrates that context affects the preference of a user in real life scenario. Similarly, user demographic data also plays an important role in our daily life [5] and online services will become more personalized if background information is taken into consideration. Therefore, researchers try to incorporate user background information into user profile as an additional feature [6]. In the case of sparse datasets, if user ratings are not available then a recommendation can be made using her demographic data. For e.g. while recommending movies, age groups are very important. Similarly, income amount is very important for suggesting tourist destinations. To get the exact human perceptions there is a need of fuzzification of user demographic information because most human perceptions are fuzzy in nature. All these external data can be considered as additional features in a user profile [7].

RELATED WORK

In the literature, there has been an extensive study on recommender systems and most of the studies used user-rated overall ratings for recommendation purpose. In this section, we provide an overview of several major sets of approaches for the suitability of our proposed framework. As we discussed in the previous section, recommender systems provide recommendation to the user based on multiple filtering techniques but broadly, it is divided into collaborative filtering [2, 3] and content-based filtering techniques, where CF works on the basis of similar like-minded users, i.e., an item will be recommended to a user if her similar users liked it in the past. Examples of such techniques that find like-minded users may cover nearest-neighbor approach [8], restricted Boltzmann machine [9], matrix completion [10], Bayesian matrix factorization [11], etc. The CF approach further classified into user collaborative filtering and item collaborative filtering [3]. User-based collaborative filtering [8] computes the similarity among the users based on the items they preferred. Then, the rating of target user's unseen item is predicted by using the combined ratings of top similar users, whereas item-based collaborative filtering [12] computes the similarity among items based on the users who preferred both items and then recommend the user those items which she preferred in the past. These two types of CF can also be combined to form user–item-based CF, which generate recommendations based on the user–item matrix by finding a common space for users and items. Matrix factorization techniques [10, 11] can be considered as the examples of user–item-based CF technique. However, CF is the widely used recommendation technique but it also suffers from multiple problems like data sparsity, cold start problem which is often referred to as new user and new items problems, which we will try to solve by proposing a user model for recommendations.

PROPOSED FRAMEWORK

The proposed framework does not depend upon the traditional user-item rating but also incorporate the user and items background information which make the system adoptable to outside rating system. In our framework the user demographical information such as user age, occupation, gender, city used. Similarly, item rating as well as the genre information was also used to take the taste from item side. The compact user model also used the contextual and situational information such as where the user experienced a particular product and what was the mood of the user at the time of using the item.

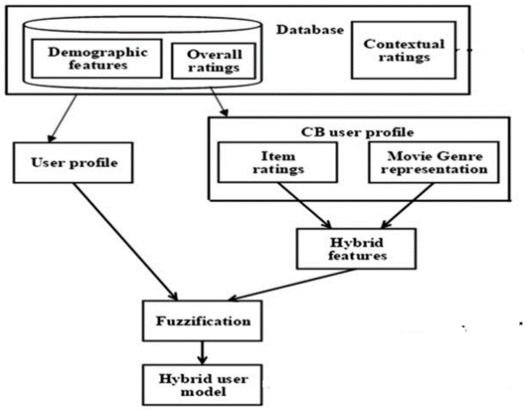

Figure 2: Proposed hybrid user framework

The user profiles were fuzzified to match the results with the real life scenario. For example, a young user will be more similar to the young age group people rather with old age group.

EXPERIMENTAL RESULTS

We have performed our experiment results on well-known MovieLens Dataset and used Mean Absolute Error performance measure to compare the traditional CF (PCCF) our proposed fuzzy based model CF (FMCF). Figure 3 shows the graphical representation of the results obtained from both user-based and item-based collaborative filtering approaches. The fuzzy model-based method FMCF shows the improved result compared to the PCCF method. Where lower the MAE value shows the better the result. Furthermore, from the results, we can clearly observe that the multi-feature based technique always have better performance than tow dimensional approaches.

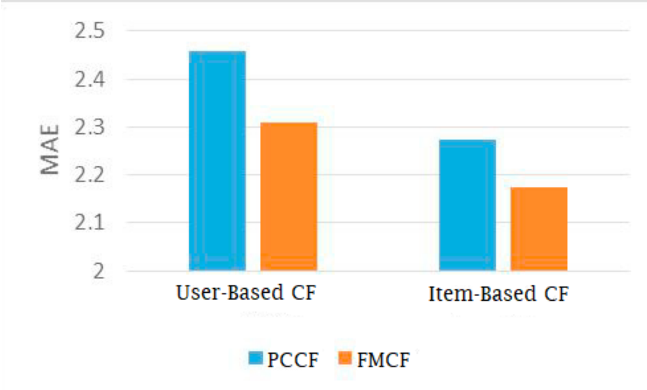

Figure 3. Comparison of Pearson correlation with fuzzy model collaborative recommenders.

CONCLUSION

In this paper, we have incorporated the user-item background features into the traditional collaborative filtering based recommender system using user model approach. Our approach handled the dimensionality problem by treating the other information as the feature of the user model. The user demographical information,

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contextual ratings and item genre information has been collected to prepare the user compact model. Results demonstrate that our proposed approach is more accurate and effective than the traditional Pearson based collaborative filtering based approach.

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