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A Survey on Recommender systems used for User Service Rating in Social Network

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Abstract - *now a days due to the growth of smart phone and tablet device users. There is a huge demand for service rating by users. Everyone rely on these service ratings in their everyday life to know about the usefulness of the particular service. Recommender systems are devised to Predict efficient user ratings. Recommender systems filter the information's from users to predict user ratings. A user –service rating prediction approach is proposed by exploring the behavior of user's rating in social network. To perform recommendation a number of techniques have been proposed, including content-based, collaborative, and hybrid techniques. In the approach of user service rating prediction four factors are fused user personal interest, interpersonal interest similarity, interpersonal rating behavior similarity and interpersonal rating behavior diffusion into a unified matrix-factorized framework*

***Key Words:* Service rating, Social networks, Recommender system, semantic mining.**

1. INTRODUCTION

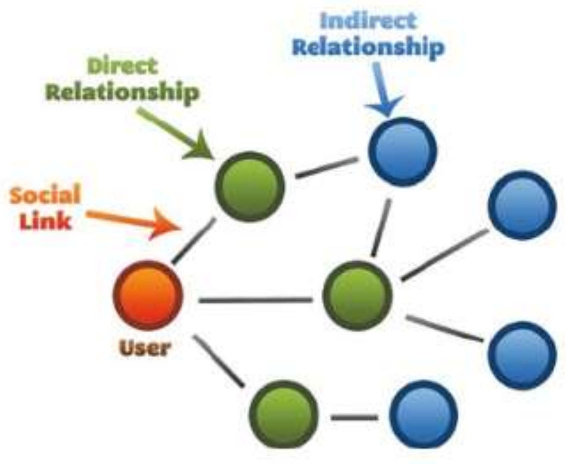
The rapid development of mobile devices gives immense access of internet and many social network services. Day by day the mobile users count increases rapidly. And the statistics says that, the smart phone user's count in India in the 2017 is 299.24 million [1]. Using the social networks which allow the users to share their opinions, reviews, suggestions and images. Due to the huge sized and dynamic data, the recommendation and suggestion is become difficult. With the help of social network data's the recommendation can be effectively performed to satisfy the users need [2**]**. The social relationships and their ratings can be used for service recommendation. In this paper we reviewed some related works, and define the demerits and usage of those techniques. Additionally the common challenges and issues in the recommender system and service exploring process are studied.

2. RELATED WORK

2.1 RECOMMENDATION SYSTEM AND TECHNIQUES

Nowadays, recommender systems are becoming one of the approaches that help users to make decision in regards of what products to buy, which news to read and what movie to watch. These systems try to maintain the loyalty of users and increase sale from producer's point of view and on the other side save user's time and money through proposing the most matched recommendations to users. [3]

Generally, three categories for recommender systems can be enumerated which are collaborative filtering, content-based filtering and the hybrid version which is the combination of two mentioned categories. Social recommender systems which are known as improved version of collaborative filtering are based on social networks. Social networks are made of a finite group of users and their relationships (figure1) that theyestablish among them through the social links so one key insight is that social-based recommender systems should account for a number of dimensions within a user's social network, including social relationship strength, expertise, and user similarity. There are several techniques to extracting information from social graph network such as information retrieval [4] and knowledge extraction [5] that can be applicable in collaborative filtering. Additionally, combining summarization techniques [7] and data mining approaches [8] with collaborative filtering model is getting more attention these days to receive a better accuracy. Analyzing the data generated by users within social networks has several practical applications that can be used to develop recommendation systems [6].



FFigure 1: the pattern of social relationship in social networks [9].

2.2 COLLABORATIVE RECOMMENDATION

There exists many collaborative recommender systems in the academe and in the industry. Grundy system presented by E. Rich (1979) [10], a librarian program was the first recommender system that proposed to build models of users based on a limited amount of information on each individuals using stereotypes. It gathers personal information through interactive dialogue, matches user responses against a database (library) of user stereotypes and recommends books. Tapestry [11], a manual collaborative filtering system presented by Goldberg *et al.* relied on each user to identify like-minded users manually. It was designed to recommend documents drawn from newsgroups to a group of users. GroupLens [12,13], Video Recommender [14], and Ringo [15] were the first automated collaborative filtering system.

The GroupLens [12,13] system was also developed for filtering text documents (i.e., news articles), but was designed for use in an open community and introduced the basic idea of automatically finding similar users in the database for making predictions. The Ringo [15] system, presented by Shardanand and Maes (1995) describes a music recommender based on collaborative filtering using Pearson's correlation measure and the mean absolute error (MAE) evaluation metric. Other examples of collaborative recommender systems include the Amazon.com book recommendation system and the Jester system [16] that recommends jokes.

According to Breese *et al.* [17], algorithms for collaborative recommendations can be grouped into two general classes: model-based and memory-based. Memory-based algorithms [13,17,18,19] are heuristics that use previously rated items by the users to make rating predictions. That is, the value of the unknown rating rc,x for item x and user c is usually computed as an aggregate of the ratings of some other (usually the N most similar) users for the same items:

rc,x=aggr rc',x

c'^C

Where C^ indicates the array of N users who have rated item s and are most similar to user c. In contrast to memory-based methods, model-based algorithms [16, 17, 19, 20, 21, 22,23] first uses a set of ratings to learn a model, then using this model make rating predictions

2.3 HYBRID RECOMMENDATION

One way to build hybrid recommender systems is to implement separate collaborative and content-based systems and then combine the outputs (ratings) obtained from individual recommender systems into one final recommendation. Daily Learner system [24] presented by Billsus & Pazzani (2000), selected the recommender system that gave the recommendation with the higher level of confidence, while hybrid recommender system presented by Tran & Cohen [25] chose the one whose recommendations were more consistent with past ratings of the user. Many hybrid recommender systems, including the "collaboration via content" approach described by M. Pazzani (1999) [26] and the Fab system [32], were based on traditional collaborative techniques but also maintained the content-based profiles for each user. Fab system [32] used content-based filtering, which ranked documents and considered user's feedback to update their personal selection agent's profile. As presented by M. Pazzani [26], this allows to overcome some sparsity-related problems of a purely collaborative approach, since typically not many users will have a substantial number of commonly rated items. Basu *et al.* (1998) [27] proposed to use content-based and collaborative characteristics (e.g., the age or gender of users or the genre of movies) in a single rule-based classifier. Popescul *et al.* [28] and Schein *et al.* [30] proposed a unified probabilistic method for combining collaborative and content-based recommendations. Several papers, such as [32, 26, 29, 30], states that hybrid approaches provide more accurate recommendations than traditional approaches by empirically comparing the performance of hybrid with collaborative and content-based approaches.

2.4 CONTENT-BASED RECOMMENDATION

G. Salton, in book "Automatic Text Processing" [40] has shown that the content-based recommendation has its roots in information retrieval and information filtering. It is due to the early advancements made by the information retrieval and filtering communities that many content-based recommenders focus on recommending items containing textual information such as URLs and documents. Fab system [32] presented by Balabanovic & Shoham (1997) recommended Web pages to users, presented 100 most important keywords in the content along with the web page content. Similarly, the Syskill & Webert system [23] presented by Billsus & Pazzani, represented documents with the 128 most informative words. There are several methods that could determine the "importance" of word in document such as Dice coefficient, probabilistic methods and explicit decision models. One of the best-known measures for specifying keyword weights is the term frequency/inverse document frequency (TF-IDF) measure [40] used by G Salton (1989). Content-based systems recommend those items that are similar to those liked by the user in the past. Pazzani & Billsus [23] used a Bayesian classifier in order to estimate the probability that a document will be liked. NewsDude [24] presented by Billsus & Pazzani (1999), a content-based filtering system suggests new stories the user might like to read. To accomplish this two user models are built. The first user model measure similarity between the new story and the stories that the user has read before by counting the co-occurrences of words appearing in these stories. The second user model assigns a probability of interest to a new story by comparing how frequently its words occur in those stories the user regards as interesting to those the user regards as of no interest.

3. EXISTING METHODOLOGY

Numerous models based on social networks have been proposed to improve recommender system performance. They

are:

1. The method of 'inferred trust circle' based on friends circle was designed by Yang [34] for the purpose of suggesting popular and number one items to users. Their approach, called the Circle Con Model, not only lessens the load of big data and estimation complexity, but also determines the relational faith in the complicated social networks.

2. Personalized travel recommendation was proposed by Chen [35] by considering user attributes and social information.

3. Jiang [10] proved that an user's individual choice is also an important aspect in social networks.

4. Herlocker et al [36] proposed a model which shows the similarity between users or items according to the number of common ratings.

5. Deshpande and Karypis [37] proposed an item-based CF combined with a condition-based probability similarity and Cosine Similarity.

4. CHALLENGES AND ISSUES

Cold start: It's challenging to give suggestions to unfamiliar users as his/her profile is almost blank and he has not rated any items and so his taste is anonymous to the system. This is known as the cold start obstacle in some recommender systems this problem is solved with survey when creating a profile. Items can have cold-start issue when they are new in the system and haven't been rated before. The above two problems can also be solved with hybrid Methods [38]

5. CONCLUSION AND FUTURE WORK

A personalized suggestion approach was proposed by combining social network factors: intimate interest, social interest similarity, and interpersonal impact. In particular, the personal interest denotes user's individuality of rating items, especially for the professional users, and these factors were combined together to improve the faultlessness and appropriateness of recommender system. We conducted extensive experiments on two large real-world social rating datasets, and showed significant development over current approaches that use mixed social network information. At current, the personalized suggestion model only takes user historical rating records and mutual relationship of social network into consideration. In our future works, we will consider user location information to suggest more personalized and real-time items [39].

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