Review on Recommended System Category and Its Applications

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Abstract- Today recommender systems become emerging field for research due to its diverse characteristics. Recommender system has number of applications. One of among it represent a powerful method for enabling users to filter through large information and web contents. Recommender Systems is also referred as software techniques providing suggestions for items to be of use to a user. The suggestions provided are aimed at supporting their users in various decision-making processes, such as what items to buy, what music to listen, or what news to read. Several methods for item recommendation from implicit feedback like matrix factorization or adaptive k-nearest-neighbor. Even though these methods are designed for the item prediction task of personalized ranking, none of them is directly optimized for ranking. In these article different recommended techniques, application and system is discussed.

Keywords- Recommended System, Application Domain, Techniques.

I. INTRODUCTION

Recommender systems became an important research area since the appearance of the first papers on collaborative filtering since the mid-1990s [45, 86, 97]. There has been much work done both in the industry and academia on developing new approaches to recommender systems over the last decade. The interest in this area still remains high because it constitutes a problem rich research area and because of the abundance of practical applications that help users to deal with information overloads and provide personalized recommendations, content and services to them. Recommender systems have been widely adopted by many online sites/services in recent years. These systems are an important mechanism for enabling users to deal with the massive information overload, since they provide suggestions of items/services, which are chosen in a way to match the user's preferences and interest [1].

II. RECOMMNEDED SYSTEM TECHNIQUES

In this section we discussed some popular techniques for recommended system. Recommender systems are usually classified into the following categories, based on how recommendations are made [2]:

- Content-Based Methods

In content-based recommendation methods, the utility of item for user is estimated based on the utilities assigned by user to items that are "similar" to item. For example, in a movie recommendation application, in order to recommend movies to user the content-based recommender system tries to understand the commonalities among the movies user has rated highly in the past (specific actors, directors, genres, subject matter, etc.)

- Collaborative Methods

Collaborative recommender systems (or collaborative filtering systems) try to predict the utility of items for a particular user based on the items previously rated by other users . For example, in a movie recommendation application, in order to recommend movies to user c , the collaborative recommender system tries to find the "peers" of user c , i.e., other users that have similar tastes in movies (rate the same movies similarly)

- Hybrid Methods

Several recommendation systems use a hybrid approach by combining collaborative and content- based methods, which helps to avoid certain limitations of content-based and collaborative systems. Different ways to combine collaborative and content-based methods into a hybrid recommender system can be classified as follows: (1) implementing collaborative and content-based methods separately and combining their predictions, (2) incorporating some content-based characteristics into a collaborative approach, (3) incorporating some collaborative characteristics into a content-based approach, and (4) constructing a general unifying model that incorporates both content-based and collaborative characteristics

III. APPLICATION DOMAIN

- Mobile Recommender System

In the paper presented by FANG et.al [3], he implemented a mobile recommender system for recommend for indoor environments. Also have been expressed, because the global positioning system (GPS) is not suitable for the indoor environments and devices equipped with GPS do not work in indoor environments, also RFID is very expensive and still should pay high costs to buy RFID readers.

- Entertainment Recommender System

In the paper presented by Ingrid A. Christensen, S. Schiaffino [4] the main problem is recommendation to group and expressed that for recommending to group we face some difficulties, also trying to recommend movie and music to the group of users. The presented system works based on a framework which called group recommendation.

- Movie Recommender System

In the paper presented by Maria S. Pera et.al [5] a group recommender called GROUPREM is proposed that use three techniques for giving recommends: Identify personal interests of group members and then merge them and creates group profile that reflects the group preferences. To find similar content movies use word correlation. Considering the popularity of movies on a website.

- The Tourist Recommender System

In the paper presented by Inma Garsia et.al [6] a framework for the recommender system has been provided and this framework is based on the tourist issue. A recommender system based on web has been proposed for tourist that provides a trip plan for Valencia City in Spain; this system is able to recommend either user or a group of users.

- Software Recommender System

In the paper presented by Enrique Costa-Montenegro et.al [7] is mentioned that users due to increasing of uncontrolled software and lake of proper classification for software, also because the software are very different, the good classification of them is not provided, and users always have difficulty in choosing the appropriate software.

- Nurse Supporter Recommender System

In the paper presented by Mei-hue Hsu [8], a mapping diagram recommender system is proposed for second language nurses which testes on Taiwanese nursing students. In this paper, data mining association rules are used in the system provided by optimum words or required terms for nursing automatically

IV. LITERATURE REVIEW

This section describes the literature on recommended system.

One of the most popular and successful techniques for recommender systems is Collaborative Filtering (CF) [9]. The main idea behind CF is that users with similar past interests will also share common interests in future. In the CF technique, two topics are studied: neighborhood models and latent factors. In the first case, clusters of item are formed to recommend items which are similar to the ones preferred by the user in the past. Alternatively, clusters of users can be formed to recommend items to a specific user, i.e. items appreciated by other users of similar preferences. In the second topic, the recommendation can be computed by uncovering latent associations among users or items. Thereby, an alternative path is comprised to transform both items and users into the same latent factor space, allowing them to be directly comparable [10].

In [11], it was proposed the latent factor algorithm gSVD++, that uses explicit (i.e., ratings provided by users to items) and implicit (i.e., interaction of the user with the item or metadata associated to the item) feedback to infer the user's preference. Although the algorithm uses both types of feedback, it is only feasible if the explicit feedback is available. This is a drawback because explicit feedback is not always available. Besides, in real world scenarios, most feedback is implicit. In order to overcome this issue, in this work we propose the MABPR gSVD++ algorithm to provide item recommendation based only on implicit feedback.

MABPR extends the Bayesian Personalized Ranking technique

(BPR) [12] to use available metadata of items (e.g., genres of movies/music, keywords, list of actors, authors, etc.) to optimize the personalized ranking of items to the user. In this way, the goal is to provide a better personalized ranking of items based only on implicit feedback

Author [13] proposed a new CF approach, Col-laborative Less-is-More Filtering (CLiMF). In CLiMF the model parameters are learned by directly maximizing the Mean Reciprocal Rank (MRR), which is a well-known information retrieval metric for capturing the performance of top-k recommendations.

Authors [14] proposed a collaborative filtering (CF) recommendation framework, which is based on viewing user feedback on products as ordinal, rather than the more common numerical view. This way, we do not need to interpret each user feedback value as a number, but only rely on the more relaxed assumption of having an order among the different feedback ratings. Such an ordinal view frequently provides a more natural reflection of the user intention when providing qualitative ratings, allowing users to have different internal scoring scales.

Authors [15] proposed the probabilistic latent preference analysis (pLPA) model for ranking predictions by directly modeling user preferences with respect to a set of items rather than the rating scores on individual items. From a user's observed ratings, we extract his preferences in the form of pairwise comparisons of items which are modeled by a mixture distribution based on Bradley- Terry model.

Authors [16] described a new family of model-based algorithms designed for learning pridictive models. These algorithms rely on a statistical modelling technique that introduces latent class variables in a mixture model setting to discover user communities and prototypical interest profiles.

Authors [17] we propose Collaborative Competitive Filtering (CCF), a framework for learning user preferences by modeling the choice process in recommender systems. CCF employs a multiplicative latent factor model to characterize the dyadic utility function. But unlike CF, CCF models the user behavior of choices by encoding a local competition effect.

Authors [18] discussed a number of extensions to MMMF by introducing offset terms, item dependent regularization and a graph kernel on the recommender graph. We show equivalence between graph kernels and the recent MMMF extensions.

Authors [19] identified unique proper- ties of implicit feedback datasets. We propose treating the data as indication of positive and negative preference associated with vastly varying confidence levels. This leads to a factor model which is especially tailored for implicit feedback recommenders. We also suggest a scalable optimization procedure, which scales linearly with the data size. The algorithm is used successfully within a recommender system for television shows.

Authors [20] considered the one class problem under the CF setting. We propose two frameworks to tackle OCCF. One is based on weighted low rank approximation; the other is based on negative example sampling.

Authors [21] focus the problem of top-N context-aware recommendation for implicit feedback scenarios. Also proposed TFMAP, a model that directly maximizes Mean Average Precision with the aim of creating an optimally ranked list of items for individual users under a given context. TFMAP uses tensor factorization to model implicit feedback data (e.g., purchases, clicks) with contextual information.

V. CONCLUSION

Recommending content is an important task in many information systems. For example online shopping websites like Amazon give each customer personalized recommendations of products that the user might be interested. Item recommendation is the task of predicting a personalized ranking on a set of items such as websites, movies, and products. The motive of the article is different recommended techniques, application and system.

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