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A Review on Personalized Approach for Solving Recommendation System Problems Combining User Interest and Social Circle

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Abstract: ***Rapid growth of information generated by online social networks leads to increase in demand of effective recommender systems to give accurate results. Traditional techniques become unqualified because they do not consider data of social relation in the social network for giving recommendation; existing social recommendation techniques consider social network structure, but social perspective has not been fully measured by these techniques. It its noteworthy and challenging to fuse social contextual factors which are derived from users' motivation of social activities into social recommendation. With the introduction and popularity of social network, ever more users like to share their real life experiences, such as blogs, ratings and reviews. New latest aspects of social networking like interpersonal influence and interest based on circles of friends carry opportunities and challenges for recommender system (RS) to resolve the cold start and sparsity problem of datasets. Several of the social factors have been used in Recommendation Systems; but still they have not been completely measured. This paper gives review on, various recommendation techniques and main three social aspects, User personal interest, interpersonal interest similarity, as well as interpersonal influence, and how these factors are fuse into a combined personalized recommendation model to give the recommendations to the user.***

Keywords: Interpersonal Influence, Personal Interest, Recommender System, Social Networks, Contextual Recommendation, User Interest Factor.

1. Introduction

Users on social networks generate large volume of information and urge recommender systems to provide useful results. Traditional techniques typically based on collaborative filtering become unqualified in solving the social recommendation problem because they ignore social relation or interaction data [1].

Besides the experiential assumptions, psychology and sociology studies have proved that individual preference and interpersonal influence affect users' decisions on information adoption. This paper demonstrates that the introduction of interpersonal influence into the preference driven decision process (as is the case in real social networks) makes user behaviors more complex and thus increases the unpredictability of the item adoption [2]. Therefore, only when individual preference and interpersonal influence are properly fused into recommendation, the impulsiveness can be reduced and the recommendation performance can be improved accordingly [1]. we propose a social contextual recommendation framework based on a probabilistic matrix factorization method to incorporate individual preference and interpersonal influence to improve the accuracy of social recommendation [1]. More specifically, we factorize the user-item interaction matrix into two intermediated latent matrices: user-item influence matrix and user-item preference matrix, which are generated from three objective latent matrices: user latent feature matrix, item latent feature matrix, and user-user influence matrix. Moreover, as we can partially observe individual preference and interpersonal influence based on historical user-item and user-user interaction data, we further utilize the observed contextual factors to compute the three objective latent matrices.

2. Literature Survey

Many social network based models [4]-[5] have been proposed to improve the performance of the RS. Recently, Yang et al. [2] propose to use the concept of 'inferred trust circle' based on the domain-obvious circles of friends on social networks to recommend user favorite items. Their approach refines the interpersonal trust in the complex networks, as well as reduces the load of big data. Meanwhile, besides the interpersonal influence, Jiang et al. [3] demonstrate that individual preference is also a significant factor in social network. Just like the indication of social influence, due to the preference similarity, user latent structures should be similar to his/her friends' based on the probabilistic matrix factorization model [6], [8]. Though, do all users actually require the relationship on the social networks to recommend items? Does the relationship suppress user's personality, especially for the skillful users? It is still a great challenge to embody user's personality in RS, and it is still an open issue that how to make the social factors be effectively integrated in recommendation model to improve the accuracy of RS.

Phelan et al. [9] proposed a news recommendation technique utilizing real-time Twitter data as the basis for ranking and recommending articles from a collection of really simple syndication feeds. And one of the conclusions is that users with more friends tend to benefit more. Chen et al. [10] explored three separate dimensions in designing such a recommender: contented causes, topic interest models for users, as well as social voting. They prove that both topic relevance and the social voting process were helpful in providing recommendations.

The quality of recommendations and usability of six online recommender systems was examined in [11]. The results show that the user's friends consistently provided better recommendations. For example 80% of users believe the book recommended is good from friends, 65% of users believe that the recommendation is useful from friends.

This research shows that the interpersonal influence is important in social media. Java et al. [12] had analyzed a large social network in a new form of social media known as micro-blogging. It has a high degree correlation and mutuality, representing close mutual friends among users. They had identified different types of user intentions and studied the community structures. Categorizing friends into groups (e.g. family, co-workers) would greatly benefit the adoption of micro-blogging platforms to analyze user intentions. That is to say user intentions or interests can be reflected by those of its friends.

Rahman and Hailes provide and discuss a model for supporting trust in virtual communities, which is based on experience and reputation [13]. We can realize the importance of user's information such as the number of ratings in every classification and his/her reputation or dependability. Yuan et al. have discovered a kind of social relation, the membership, and its joint effect with friendship. The two types of heterogeneous social relations are fused into the Collaborative Filtering based recommender via a factorization process. And the distinguished effectiveness of social relationships in the sparse data condition was demonstrated.

In the following description, we have given review on some relevant works to this paper, including the basic matrix factorization model [6] without any social factors, the CircleCon model [2] with the factor of interpersonal trust values as well as the Social Contextual (ContextMF) model [3] with interpersonal influence and individual preference, The Personalized Recommendation Model Combining User Interest and Social Circle [1].

2.1 Basic Matrix Factorization

(BaseMF) approach, which does not take any social factors into consideration. The task of RS is to decrease the error of predicted value using **R** to the real rating value. Thus, the BaseMF model is trained on the observed rating data by minimizing the objective function[1] [2]-[4].

2.2 CircleCon Model

The CircleCon model has been found to outperform BaseMF and SocialMF with respect to accuracy of the RS. The approach focuses on the factor of interpersonal trust in social network and infers the trust circle[2]-[4].
Procedure:

1] Trust circle inference
We infer the circles of friends from rating (or other feed-back) data concerning items that can be divided into different categories (or genres etc.). The basic idea is that a user may trust each friend only concerning certain item categories but not regarding others. For instance, the circle of friends concerning cars may differ significantly from the circle regarding kids' TV shows [2].

2] Trust value assignment
The trust values between friends in the same inferred circle (based on item category c) are captured in a social network Matrix. In the following, we consider three variants of defining the positive values when user v is in the inferred circle of user u regarding category c [2].

- CircleCon1: Equal Trust
- CircleCon2: Expertise-based Trust
- CircleCon3: Trust Splitting

3] Model training
-Training with ratings from each category
-Training with ratings for all categories [2].

2.3 ContextMF Model

Jiang et al. [1][3] demonstrate the significance of social contextual factors (including interpersonal influence and individual preference) for item adopting on real Facebook and Twitter style datasets. The task of ContextMF model in [3] is to recommend acceptable items from sender u to receiver v.

Here, the aspect of interpersonal influence is similar to the trust beliefs in CircleCon model [3]. Besides the interpersonal influence (similar to the trust values in CircleCon model [2]), individual preference is a novel factor in ContextMF model. Note that we still execute the interpersonal influence as CircleCon model [2] and omit the topic relevance of items, as we also predict ratings of items in Epinions style datasets and use the circle based idea in our experiments. Although individual preference is proposed in this model, user u's latent feature is still connected with his/her friends rather than his/her Characteristic.

In fact, the factor of singular preference of this model is enforced by interpersonal preference similarity.
Matching ContextMF model, the proposed personalized recommendation model has three differences:

1) The job of our model is to recommend user, regardless of sender or receiver, interested and unknown items.
2) User personal interest is directly related to his/her rated items rather than connect with his/her friends.
3) The reason of user interest in our model mined from user rated items has more influence than individual preference in ContextMF model, because it easier for the recommended items of our model to be transformed into purchase rate than the adopted items in Facebook style social networks.

3. The Existing Approach Considered As Base for Proposed System

The personalized recommendation approach rages three social factors: user personal interest, interpersonal interest similarity, and interpersonal influence to recommend user interested items. The illustration of our approach is shown in Fig. 1. Among the three factors, user personal interest and interpersonal interest similarity are the main contributions of the approach and all related to user interest. Thus, we introduce user interest factor firstly. And then, we infer the objective function of the proposed personalized recommendation model [1].

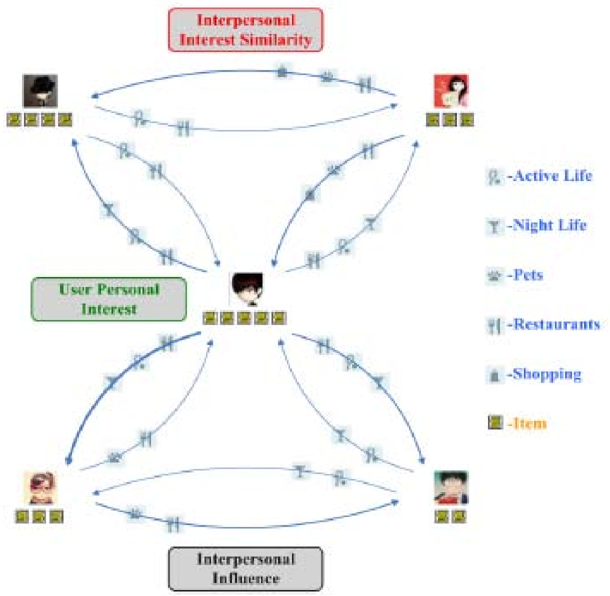

Figure 1: Three main social factors in recommendation model, including user personal interest, interpersonal interest similarity, and interpersonal influence. The items under users are historical rating records, which can be used to mine users' personal interest. The category icon on line between two users denotes their interest similarity and the boldness of the line between users indicates the strength of interpersonal influence (Existing system Demonstration).

3.1 User Interest Factor

Besides the trust values between friends in the same category [2], user interest is another significant factor to affect users' decision-making process, which has been proved by psychology and sociology studies. Moreover, Jiang et al. [3] demonstrated the effect of ContextMF model with consideration of both individual preference and interpersonal influence. However, there are two main differences of the user interest factor in our model to individual preference in ContextMF [3]:

1) The independence of user interest. It means we can recommend items based on user interest at a certain extent. In other words, we utilize user's connection with the items to train the latent feature vectors, especially for the experienced users.
2) Interest circle inference. Just like CircleCon model [2], we divide the tested social network into several sub-networks, and each of them corresponds to a signal category of items. Considering the cold start users who has a few rating records, we use friends' interest in the same category to link user latent feature vector.

3.1.1 User Interest Description

According to the natural item category tags of rating datasets, we can get category distribution of the item.

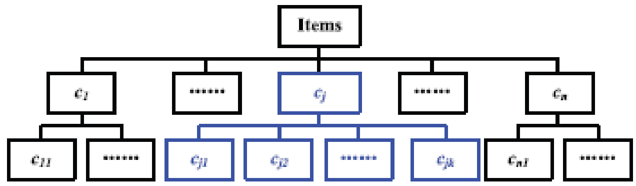

Figure 2: Tree structure of categories of items

The first level of the tree structure is the big category of items. The second level is the subcategory of each big category in the first level. We get two level topic distributions of each item in the datasets corresponding to the two level of the tree
Thus we measure user interest which having different meaning [1].

3.1.2 Personal Interest

Due to the individuality, especially users with many rating records, users usually choose items all by themselves with little influence by their friends. However, many previous works [2]–[4] took the circles of friends in social networks to solve the cold start problem. It did work for the cold start users with a few records, but ignored the individuality for experienced users. In other words, the relevance of user and item latent feature vector depends on the relevance of user interest Du and item topic Di to a certain extent.

More formally, we denote the relevance of user u's personal interest to the topic of item i in our recommendation model by Qu,i = Sim(Du,Di).

3.1.3 Interest Circle Inference

Similar to the trust circle inference in CircleCon model [2], we propose the interest circle inference. The basic idea is that user latent feature vector should be similar to his/her friends' latent feature vector based on the similarity of their interest.

Thus User Interest Factor includes the following information about the User:

- User interest description
- Personal interest
- Interest circle inference

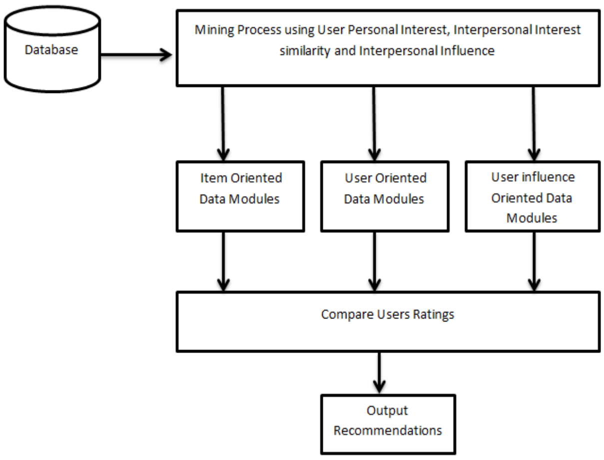

Figure 3: Systems Architecture

4. Personalized Recommendation Model (Proposed System)

As the main aim of our method is to give accurate recommendations to the users according to user's personal interest, so we will combine user interest and social circle in such a way that, it will give better recommendations than the previous recommendation techniques. So our proposed recommendation system will contain following modules:

4.1. User Interest Factor:

- User interest description
- Personal interest
- Interest circle inference

Aim of our system is to give accurate recommendations to the user on the basis of its personal interest. So, in order to give accurate recommendations to the user, we have to find exactly what the user wants. To do this we have to scan/extract the user interest or user query. So for that purpose we have to do the feature extraction. In this user inputs a query to system, the query is stored in to database. And after this the various features are extracted from that query.

There are various feature extraction algorithms. Among these feature extraction algorithms it is not possible tell which one is best. So, we have to use the feature extraction algorithm according our need. Here we will perform the dynamic feature extraction

4.2. Mining Data

- Item oriented data modules
- User oriented data modules
- User influence oriented data modules

4.2.1. Mining Item oriented Data modules

By using user interest description we define user's personal interest. and using this personal interest related to items, we scan the database for the item for which a particular user is interested in.

4.2.2. Mining user oriented Data modules

In this, we will take in to consideration the individual user interest as well as other users interest and compare them by using collaborative filtering technique and by using this user oriented data, we will scan the database.

4.2.3 Mining user influence oriented Data modules

In this, we will mine the database on the basis of individual user interest which is influenced by other user's interest which are in similar social circle.

4.3 Dynamic mining of weighted ratings on the basis of user preferences

In this, we will take the user preferences item oriented mining, user oriented mining and user influence oriented mining process, which are then combined. And after this particular weight is assigned to these user ratings and by using this data personalized recommendations are given to the user.

After finding the user oriented, user similarity and inter personal influence oriented data, next task is to combine all these data and arrange this data according to similarity with user personal interest and give the recommendations to the users. For this purpose we will use BiClustering and Fusion Technique. The Output of this step will be the output of our proposed system, i.e. Recommendations.

5. Conclusion

This paper provides various existing methods used for personalized recommendation. By reviewing these recommendation techniques it is observed that, In most of the recommendation techniques Cold start problem and Sparsity problem of Data set occurs.

So, to overcome these problems we have proposed some modifications in a personalized recommendation technique in which we can use a BiClustering and Fusion Technique at the end of previous personalized recommendation technique. It will give the accurate recommendations according to user personal interest and it will also solve the problem of Cold start user and sparsity of Datasets in effective manner.

References

[1] Xueming Qian, Member, IEEE, He Feng, Guoshuai Zhao, and Tao Mei, Senior Member, IEEE:I" Personalized Recommendations combining user interest and Social circle", IEEE transactions on knowledge and data engineering, vol. 26, no. 7, July 2014

[2] X.-W. Yang, H. Steck, and Y. Liu, "Circle-based recommendation in online social networks," in Proc. 18th ACM SIGKDD Int. Conf. KDD, New York, NY, USA, Aug. 2012, pp. 1267–1275.

[3] M. Jiang et al., "Social contextual recommendation," in Proc. 21st ACM Int. CIKM, New York, NY, USA, 2012, pp. 45–54.

[4] M. Jamali and M. Ester, "A matrix factorization technique with trust propagation for recommendation in

social networks," in Proc. ACM Conf. RecSys, Barcelona, Spain, 2010, pp. 135–142.
[5] F. Liu and H. Lee, "Use of social network information to enhance collaborative filtering performance," Expert Syst. Appl., vol. 37, no. 7, pp. 4772–4778, Jul. 2010.
[6] R. Salakhutdinov and A. Mnih, "Probabilistic matrix factorization," in Proc. NIPS, 2008.
[7] J. Huang, X. Cheng, J. Guo, H. Shen, and K. Yang, "Social recommendation with interpersonal influence," in Proc. 19th ECAI, Amsterdam, Netherlands, pp. 601–606, 2010.
[8] M. Ou et al., "Comparing apples to oranges: A scalable solution with heterogeneous hashing," in Proc. 19th ACM SIGKDD, Chicago, IL, USA, 2013.
[9] O. Phelan, K. McCarthy, and B. Smyth, "Using twitter to recommend real-time topical news," in Proc. 3rd ACM Conf. Recommender Systems, Hong Kong, China, 2009, pp. 385–388.
[10] J. Chen, R. Nairn, L. Nelson, M. Bernstein, and E. Chi, "Short and tweet: Experiments on recommending content from information streams," in Proc. 28th Int. Conf. Human Factors Computing Systems, Atlanta, GA, USA, 2010, pp. 1185–1194.
[11] R. Sinha and K. Swearingen, "Comparing recommendations by online systems and friends," in Proc. DELOS Workshop Personalization Recommender Systems Digital Libraries, Dublin, Ireland, 2001.
[12] A. Java, X. Song, T. Finin, and B. Tseng, "Why we twitter: Understanding micro blogging usage and communities," in Proc. 9th WebMD, 1st SNA-KDD, San Jose, CA, USA, 2007, pp. 56–65.
[13] A. Rahman and S. Hailes, "Supporting trust in virtual communities," in Proc. 33rd Int. Conf. System Sciences, Maui, HW, USA, 2000

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