Volume : 5 | Issue : 1 | JANUARY 2016 • ISSN No 2277 - 8179

Research Paper

Review of Personalized Recommendation System With User Interest in Social Network

Engineering

KEYWORDS : Social Network, Recommendation system, Personalized Recommendation System, User Personal interest, Interpersonal interest similarity, Interpersonal Influence.

Santosh Dange

ME Student, Department of Computer Engineering, RMD Sinhgad School of Engineering, Savitribai Phule, Pune University, India

ABSTRACT

Recommendation System (RS) is the tool, which help to find interesting and relevant items or products. With the 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. The potential growth of the internet results the use of social networks such as Facebook, Twitter, linked-in etc. which produces huge amount of information (data), which leads to overwhelming. To overcome overwhelming, Personalized Recommendation System have been expansively used. In this paper, we discussed importance of Recommendation Systems, different methodologies and social factors, which influence Personalized Recommendation System.

I. INTRODUCTION

Recommendation system (RS) has been successfully used to solve problem overwhelming. Social networks such as facebook, twitter are handling large scale of information by recommending user interested items and products. RS has wide range of applications such as research articles, new social tags, movies, music etc. According to the user input and different attribute items can be recommended, which is closely related to user interst.

Survey shows that more than 25 percent of sales generated through recommendation. Over 90% peoples believe that products recommended by friend are useful [1] and 50% people buy the recommended products or items of their interest. Google+ introduced "Friends Circle" to filter the contacts according to different activities and strategies [2], which helps users to be closer to their friends. In a large web space, recommendation helps to find items of user interest [4]. Collaborative filtering and content based filtering are widely used methodologies for recommendation [3]. For Data Mining works cold start has been a serious problem. Even though we have many algorithms to work on Data Mining, cold start has made people to step back in analyzing the functionality of those algorithms lead to little decrease in creativity and optimizations in data mining algorithms[4][5]. Cold start can be described as unavailability of data for modelling algorithms [5]. Web is always dynamic, so it is very difficult to predict the user interested items in time.

Personalized RS constitutes factors such as interpersonal interest, person's interest and interpersonal influence [1]. Personalized RS is helpful to recommend the items on social networks with the aim that recommended items should based on their historical behavior and interpersonal relationship of social networks. The increasingly popular online social networks provide additional information to enhance pure rating-based RS [2]. Recommendation in traditional system focuses on pair of (buyer, item) whereas social recommendation focuses on triplet (seller, buyer, item) which enhances the more appropriate items of user interest [4]. The quality of the recommendation can be achieved with the help of user interpersonal interest in social network [2]. Several social-trust based RS have recently been proposed to improve recommendation accuracy. The interpersonal relationship in the friend's circle of social networks and social contexts [1] helps to solve cold start and sparsity problem.

II. OVERVIEW OF THE TECHNIQUES

A. Cold Start Problem

Cold start problem refers to the situation when a new user or items newly added to the system [7]. With rapid increasing of registered users various products, the problem of cold start occur [8]. Three kinds of cold start problems are: new user problem, new item problem and new system problem [8]. In such cases, it is very difficult to provide recommendation, as in case of new user, there is very less information about user that is available. For a new item, no ratings are usually available. and thus collaborative filtering cannot make useful recommendations in case of new item as well as new user. For the new system, it is difficult to find the pattern [6] as there is very less information about user and newly added product or items. Most important factor in social network is individual preferences and interpersonal relations such as "friend circle" [1] helps to solve the cold start problem.

B. Sparsity Problem

Sparsity problem is one of the major problems encountered by recommender system is data sparsity of the influence on the quality [1] of recommendation. The main reason behind data sparsity is that most users do not rate most of the items and the available ratings are usually sparse. In collaborative filtering [2] technique it is important that the more users are required to be rated the item. Though high rating [6] given by few users leads to problem of sparsity. To prevail over the sparsity problem, one can use user profile information [6] while calculating user similarity item with others. Similarity in users can be identified with the aid of age, area code, gender, demographic segment etc. Sparsity problem also resolved by associative retrieval framework and related spreading activation algorithms [1]. Sparse rating matrix can used to resolve the sparsity problem. Item based mining and associative retrieval technique [5] also used to overcome the problem of sparsity.

C. Basic Matrix Factorization

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].

D. ContextMF Model

Social contextual factors 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, 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 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.

IV. PROPOSED SYSTEM

The personalized recommendation approachs there are three social factors: 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. The proposed personalized recommendation approach fuses three social factors: user personal interest, interpersonal interest similarity, and interpersonal influence to recommend user interested items. 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. At last, we give the training approach of the model. Here in after we turn to the details of our approach.

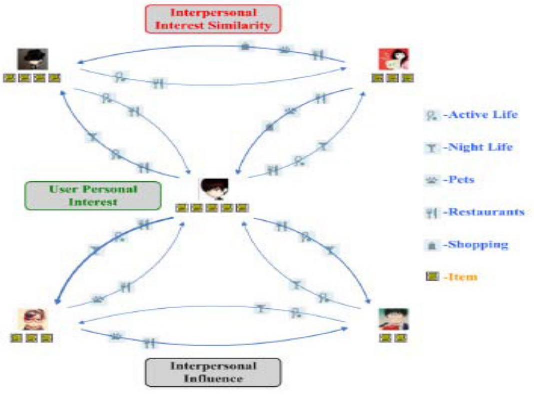

Figure 1: The main aim of our method is to give accurate recommendations to the users according to user's personal interest, so we will combine user interest and social circle in such a way that, it will give better recommendations than the previous recommendation techniques.

So our proposed recommendation system will contain following modules:

1.Item oriented data modules
2.User oriented data modules
3.User influence oriented data modules

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 particular users interested in.

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.

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.

TABEL 2
ALGORITHM OF PERSONALIZED RECOMMENDATION

Algorithm of Personalized Recommendation Model (PRM)
Initialization: $\Psi^c(0) = \Psi^c(\boldsymbol{U}^c(0), \boldsymbol{P}^c(0))$.
Require: $0<l<1$, $t=0$.
while($t<1000$)
calculate $\frac{\partial \Psi^c(t)}{\partial \boldsymbol{U}^c}$, $\frac{\partial \Psi^c(t)}{\partial \boldsymbol{P}^c}$
search optimal l
$\boldsymbol{U}^c(t)=\boldsymbol{U}^c(t)\text{-}l\frac{\partial \Psi^c(t)}{\partial \boldsymbol{U}^c}$, $\boldsymbol{P}^c(t)=\boldsymbol{P}^c(t)\text{-}l\frac{\partial \Psi^c(t)}{\partial \boldsymbol{P}^c}$
If ($\Psi^c(t) < \varepsilon$)
break;
t++;
end

CONCLUSION

To existing methods used to provide personalized recommendation system. 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 at the end of previous personalized recommendation system. It will give the accurate recommendations according to user personal interest and it will solve the problem of Cold start user and sparsity of Datasets in effective manner.

REFERENCE

| [1] X Qian, H Feng, G Zhao, T Mei "Personalized Recommendation Combining User Interest and Social Circle", Knowledge and Data Engineering, IEEE Transactions, 2014. | [2] X.W.Yang, H. Steck, and Y. Liu."Circle-based recommendation in online social networks". KDD'12, pp. 1267-1275, Aug.2012. | [3] M. Jiang, P. Cui, R. Liu, Q. Yang, F. Wang, W. -W. Zhu and S. -Q. Yang. "Social contextual recommendation". CIKM'12, pp. 45-54,2012. | [4] M. Jamali and M. Ester. "A matrix factorization technique with trust propagation for recommendation in social networks". In Proc. ACM conference on Recommender systems (RecSys), 2010. | [5] R. Salakhutdinov and A. Mnih, "Probabilistic matrix factorization," in Proc. NIPS, 2008. | [6] 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. | [7] M. Ou et al., "Comparing apples to oranges: A scalable solution with heterogeneous hashing," in Proc. 19th ACM SIGKDD, Chicago, IL, USA, 2013. | [8] 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. | [9] 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. |