A SURVEY ON TRUST BASED RECOMMENDATION SYSTEMS

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Abstract - *Recommendation systems are used to provide high quality recommendations to the users from large amount of choices. Accurate and quality recommendation is necessary in E-commerce sites. One of the most popular technique to implement a recommendation system is Collaborative Filtering (CF) [1]. It tries to find users similar to an active user and recommend him/her the items liked by these similar users. By the advent of social networks, social network based recommendation arised. In this technique a social network is constructed among the users and recommends users based on the ratings of the users who have direct or indirect social relation with the user. One of the most important benefit of social network approach is that it reduces cold start problem [1] [9].*

***Key Words* : Recommender systems, collaborative filtering, trust networks, trust Propogation, matrix factorization.**

1. INTRODUCTION

With the rapidly growing information available on internet, it is necessary to have tools to help users to select the relevant information. Recommender systems can select the online information relevant to a given user. In a recommender system, there is a set of users and set of items. A user can rate the items by giving some value and the recommendation system predicts the ratings a user given to an unknown item or recommends item based on ratings already exist. Mainly there are two types of recommendation systems: Memory based [1] and Model based systems [2] [8] [9]. Memory based algorithms use user-item rating matrix [2] and recommend based on the ratings of the item by set of similar users. Model based systems [1][8] learn and store only the parameters of the model. Model based approach is fast once the parameters are learnt but consist of a training phase which is a bottleneck. Memory based system is very slow in prediction but not include any training phase. Collaborative filtering (CF) is one of the most popular technique used in recommender systems. It recommends by assuming that users with similar preference in the past are more likely to prefer the same items in the future. But actually CF suffers from two well known issues: data sparsity and cold start problem [1]. Data sparsity is users rate a small portion of items and cold start problem is new users gives few ratings. Data sparsity and cold start problem degrades the efficiency and accuracy of the recommender system in predicting the rating of an unknown item. With the advent of social networks, there emerged social trust network based recommender systems [1]. It assumes a social network among the users and recommends a user based on the rating provided by users that have a direct/indirect social relation with the given user. It uses trust aware recommendation [1]. Trust is a heterogeneous concept in the field of social science and Trust can provide additional information to model the user preferences. Trust is one's belief towards the ability of others in providing valuable ratings. Mainly there are two types of trust: explicit trust and implicit trust [9]. Former trust is inferred from user ratings. Latter trust is directly specified by users and it indicates to whom and to what extent they trust.

1.1 LITERATURE SURVEY

Trust-aware recommender systems have been widely studied because social trust provides an alternative view of user preferences other than item ratings. Incorporating social trust can improve performance of recommendations.

P. Massa and P. Avesani [1] proposes a Trust-aware Recommender System. Recommender Systems based on Collaborative Filtering suggest user's items they might like. However due to the data sparsity of input ratings matrix, the step of finding similar users often fails. This paper propose to replace it with the use of a trust metric, an algorithm able to propagate trust over trust network. It also estimates a trust weight that can be used in place similarity weight. In the first step we find the neighbours and in second step system predicts ratings based on a weighted sum of ratings given by neighbours to items. The weight can be derived from the user similarity assessment or with use of a trust metric. The results indicate that trust is very effective in solving RSs weaknesses.

M. Jamali and M. Ester [2] explores a model-based approach for recommendation in social networks, which uses a matrix factorization technique. The latent characteristics of users and items are learned and predict the ratings a user give to an unknown item. For incorporating the trust propagation a novel SocialMF model is proposed. The SocialMF model addresses the transitivity of trust in social network by considering the trust propogation in the network. Because social influence behavior of a user is affected by his direct neighbors. Therefore feature vector of each direct neighbor is dependent on feature vector of his direct neighbors. Even if a user has not expressed any ratings, his feature vectors can be learnt as long as he is connected to the social network via a social relation. Thus SocialMF deals better with cold start users than existing methods.

Lei Guo et.al [3] proposes a probabilistic matrix factorization method named mTrustMF. Traditionally, trust-aware recommendation methods using trust relations for recommender systems assume a single type of trust between users. Actually this assumption is ignoring the fact trust as a social concept inherently has many aspects. In multi category recommender systems, users place trust differently to different people. To solve above problem, this paper proposes to fuse the user's category information with the rating matrix. This paper proposes a probabilistic factor analysis technique, that learns the multifaceted trust relations through a shared user latent feature space. The user latent feature space in user categories is the same in the rating matrix.

Tong Zhao et.al [4] investigates the potential correlation between the tags of items and trust relations between users. An algorithm based on probabilistic matrix factorization, topic-specific trust-based matrix factorization (TTMF) is proposed to use multi faceted trust relations. Only by understanding features of their chosen items can we investigate user interests and distinguish their multi-faceted trust more precisely. Based on this intuition, in this work, TTMF mine topics from tags of the items and estimate topic specific trust relations between users simultaneously. Using this topic-specific trust relations improve the recommendation accuracy and solve the item cold start problem.

W. Yao et.al [5] proposes a model, RoRec to learn dual role preferences for trust-aware recommendation by modeling explicit interactions and implicit interactions of users. Users in trust rating networks are associated with two different roles simultaneously. They are truster and trustee. "Truster" is one who trusts others and "Trustees" is one who are trusted by others. As a truster, one will be more likely affected by the existing ratings or reviews provided by other users he/she trusts, and in the same way, as a trustee, his/her contributions (ratings or reviews) will consequently affect others who trust him/her. The preferences of the two roles of users can be distinct from each other. E.g., for a digital product specialist who just wants to learn cooking, he/she is more likely to trust lots of chefs while being trusted by many digital products consumers. Hence, when predicting user preferences for an item, it is reasonable to consider both truster and trustee preferences.

Haifeng Liu et.al [6] proposes a collaborative filtering method CF-TC. In trust network-based recommender systems, there exist generally two roles for users, truster and trustee. Most of trust-based methods generally use the explicit link between the truster and trustee to find similar neighbors for recommendation. However, there will be exist implicit correlations between users, especially for users with same role. The proposed CF-TC method mainly includes two components: (i) mine implicit correlations between users with the same role (ii) apply the mined implicit correlations for rating prediction of the user. At first step, for each user, we build his user representation using those users who have same role with the user. We can obtain the weight of each implicit correlation by measuring cosine similarity between any two users with the same role. At the second step, based on the computed weights, presented two variants of CF-TC, Memory-based CF-TC and Matrix Factorization-based CF-TC.

Hao Ma, Michael R. Lyu et.al [7] studied how to effectively and efficiently incorporate the trust and distrust information into the recommender systems Based on the intuition that the distrust information is important as the trust information, in this paper the trust and distrust constraints are regularized. In order to generate better prediction quality, the trust and distrust relations between users are modeled by adding the regularization terms into objective function of the user-item matrix factorization. By performing a simple gradient on the objective function and we can learn the latent low-dimensional user-specific and item-specific matrices for prediction of the user's favors on different items.

H. Fang, Y. Bao, and J. Zhang [8] proposes a latent factor model that identifies more effective aspects of the trust for recommender systems. Main aim is to bridge the gap between trust and user preference-similarity and to adopt trust information more effectively. By decomposing the explicit trust values to finer-grained trust aspects, we can derive more effective information for recommendation. In this paper they identified four general aspects of trust (i.e. benevolence, integrity, competence and predictability) and modeled them based on users' past ratings. The four aspects are combined to a Support Vector Regression (SVR) model for trust value prediction between two users. They incorporated the trust information into the probabilistic matrix factorization model using the trust value obtained from the SVR model and by measuring similarity between the corresponding latent feature vectors factorized from rating matrix of the user. Thus, we can re-interpret the trust value for the recommendation, and surely can update user's latent feature vector by considering social influence of other users trusting and being trusted by the user.

G. Guo, J. Zhang et.al [9] proposes a novel trust-based recommendation model TrustSVD. This trust-based matrix factorization model incorporated both rating and trust information for rating prediction. Trust information is very sparse, yet complementary to rating information. So focusing too much on either one kind of information achieves only marginal gains in predictive accuracy. Also users are strongly correlated with their trust neighbors and have a weakly positive correlation with their trust-alike neighbors (e.g., friends). These observations motivated to consider both explicit and implicit influence of ratings and of trust in a trust-based model. A weighted λ- regularization technique was used to further regularize the user- and item-specific latent feature vectors. This ensures that user-specific vectors can be learned from their trust information even if a few or no ratings are given. Thus data sparsity and cold start issues for recommendation can be better solved. TrustSVD can outperform both trust and ratings based methods in the predictive accuracy.

X. Yang, H. Steck, and Y. Liu [10] presented a novel approach to improve the recommendation accuracy by introducing the concept of "inferred circles of friends". The idea is to determine the best subset of a user's friends for making recommendations in an item category of interest. As these inferred circles dependent on the various item categories, they may differ from the explicit circles of that is popular in social networks (e.g. Circles in Google+ or Facebook). They may not correspond to particular item categories that a recommender system may be concerned with. So inferred circles may be of value by themselves. For that uses a set of algorithms to find out category specific circles of friends and to infer the trust value on each link based on user rating activities in each category. To infer the trust value of a link in a circle, we first estimate a user's expertise level in a category based on the rating activities of the user as well as all users trusting him. We then assign to users trust values proportional to their expertise levels. These reconstructed trust circles are then used to develop a low-rank matrix factorization type of Recommendation systems. Circle-based RS can achieve more accurate recommendation than the traditional matrix factorization approaches that do not use any social trust information, and that use mixed social trust information across all categories.

3. CONCLUSIONS

Recommender systems are emerging as tools of choice to select online information relevant to a given user. Collaborative filtering is one of the most popular approach to building recommender systems and has successfully employed in many of the applications. But main problems of collaborative filtering are data sparsity and cold start problem. With the advent of social networking sites exploiting the information hidden in social networks to predict behavior of the users have become very important. This approach assumes a social network among users and makes recommendations for a user based on the ratings provided by the users having a direct or indirect relationship with the user. The items appreciated by the trusted users are recommended to a active user. The ratings of the trusted users are used to predict the rating a user give to an unknown item. It is observed that incorporating trust information solve the problems of collaborative filtering and also improve the efficiency and accuracy of the recommendation system. In this paper the different trust based models has been discussed.

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