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RECOMMENDED SYSTEM OF COLLABORATIVE FILTERING BASED IN SOCIAL NETWORKS

P. RAM MOHAN RAO[1] AND A. MOUNIKA[2]

[1,2]Department of Computer Science and Engineering
MLR Institute of Technology
Hyderabad, 500043, INDIA

ABSTRACT: Sharing Information Among Friends Using different online Social Network such as What's Up ,Twitter Face book between two are more friends not only sharing profile update ,Audio, Videos with her ,his direct friends are mutual Friends ,Online Social Network connect with globally direct are Indirect Friends Using Online social network sharing any product are comment and ranking it process Unique Challenge and opportunities for recommendation. This Experiment with real online voting trace and we demonstrate the OSN Network group of people seeing the Information online voting and their personal opinion will be Shared in that OSN Network Scalability and Real information gathered from their personal friend and mutual friend feedback participate in online Voting process. In our experiments End to end user information we know that we can simply identify the fake user are Real user can while users interest for hot voting can be better mined then we further purpose a hybrid RS bagging different approaches to achieve the best top-k hit.

Key Words: Online Social Networks (OSNs), Collaborative Filtering, Recommended Systems (RSs), Social Voting, KNN

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1. INTRODUCTION

Online social networks, such as Face book What's Up and Twitter, facilitate easy information sharing among friends. the *social* voting function, through which a user can share with friends her opinions, e.g., like or dislike, on various subjects, ranging from user statuses, profile pictures, to games played products purchased, websites visited, and so on. Taking like– dislike type of voting's one step further, some OSNs, e.g., empower users to initiate their own voting campaigns, on any topic of their interests, with user customized voting options. The friends of a voting initiator can participate in the campaign or retweet the campaign to their friends. Other than stimulating social interactions, social voting also has many potential commercial values. Advertisers can initiate voting's to advertise certain brands. Product managers can initiate voting's to conduct market research. E-commerce owners can strategically launch voting's to attract more online customers. The increasing popularity of social voting immediately brings forth the "information overload" problem: a user can be easily overwhelmed by various voting's that were initiated, participated, or rewetted by her direct and indirect friends. It is critical and challenging to present the "right voting's to the "right users" so as to improve user experience and maximize user engagement in social voting's. RSs work on information overload and also suggest the users about the items of their interests. In this paper, we present our recent effort on developing RSs for online social voting's, i.e., recommending interesting voting campaigns to users. Different from the traditional items for Recommendation, such as books and movies, social voting's propagating along social links. A user is more likely to be exposed to a voting if the voting was initialized, participated, or rewetted by her friends. A voting's visibility to a user is highly correlated with the voting activities in her social neighborhood. Social propagation also makes social influence more prominent: a user is more likely to participate in a voting if her friends have participated in the voting. Due to social propagation and social influence, a user's voting behavior is strongly correlated with her social friends. Social voting poses unique challenges and opportunities for RSs utilizing social trust information Furthermore; voting participation data are binary without negative samples.

It is, therefore, intriguing to develop RSs for social voting. Toward addressing these challenges, we develop a set of novel RS models; including matrix-factorization (MF)-based models and nearest-neighbor (NN)-based models, to learn user-voting interests by simultaneously mining information on user-voting participation, user–user friendship, and user group affliction. We systematically evaluate and compare the performance of the proposed models using real social voting of traces collected from the contribution of this paper it is here fold.

1) Online social voting has not been much investigated to our knowledge. We develop MF-based and NN-based RS models. We show through experiments with real social voting traces that both social network information and group affiliation information can be mined to significantly improve the accuracy of popularity-based

voting recommendation.

2) Our experiments on NN-based models suggest that social network information dominates group affiliation information. And social and group information is more valuable to cold users than to heavy users.

3) We show that simple meta path-based NN models outperform computation-intensive MF models in hot-voting recommendation, while users' interests for non hot voting's can be better mined by MF models. The rest of this paper is organized as follows presents the related work. We provide a quick overview on the social voting function of Sina Weibo and present measurement results of our data set in Section III. In Section IV, we first develop a multichannel MF model that simultaneously mines user-voting, user–user, and user-group information. We then propose several NN models based on different Meta paths in the heterogeneous information network. Experimental results are presented

2. RELATED WORK

Bond et al. Conducted a 61-million-person experiment about social influence on Face book during the 2010 U.S. congressional elections. They demonstrated that strong ties in SNs can influence people's adoption of voting activities. Different from, we study social influence on user's adoption of online social voting's, which are initiated and propagate purely in OSNs. Collaborative filtering-based RSs use user feedback data to predict user interests, leading to very accurate recommendations Adomavicius and Tuzhilin presented a survey of RSs. Koren and Salakhutdinov and Minho proposed MF-based models for rating prediction. Ceremonies et al and Shi et al. Studied collaborative filtering for top-k recommendation. Rendle et al. Presented a generic optimization criterion Bayesian Personalized Ranking (BPR)-Optimization (Opt) derived from the maximum posterior estimator for optimal personalized ranking. Rundle et al. [31] proposed a generic learning algorithm Learn BPR to optimize BPR-Opt. BPR can work on top of our proposed methods, such as Weibo-MF and NN approaches to optimize their performance. The increasingly popular OSNs provide additional information to enhance pure rating-based RSs. There are many previous studies concerning how to integrate social network information to increase recommendation accuracy, just to name a few proposed 1In this paper, we define users with less than five voting's as cold users and with more than ten voting's as heavy users. We define voting's that attract no less than 1000 users as hot voting's and less than 10 users as cold voting's.

To factorize user-item rating matrix and user–user relationship matrix together for item rating prediction. Ma et al. [30] claimed that a user's rating of an item is influenced by his/her friends. A user's rating to an item consists of two parts, the user's own rating of the item and the user's friends' ratings of the item. The authors then proposed to combine the two ratings linearly to get a final predicted rating. Jamali and Ester claimed that a user's interest is influenced by his/her friends. Thus, a user's latent features constrained to be similar to his/her friends' latent features in the process of MF.

Yang et al. claimed that a user's interest is multifaceted and proposed to split the original social network into circles. Difference circles are used to predict ratings of items in different categories. Jiang et al addressed utilizing information from multiple platforms to understand user's needs in a comprehensive way. In explicit, they planned a semi supervised transfer learning methodology in RS to deal with the matter of cross-platform behavior prediction that absolutely exploits the little variety of overlapped crowds to bridge the data across totally different platforms. Jiang et al thought-about enriching data for correct user-item link prediction by representing a social network as a star-structured hybrid graph targeted on a social domain, that connects with alternative item domains to assist improve the prediction accuracy. Moreover, context awareness is additionally a very important live to facilitate recommendation. For example, Sun proposed a collaborative now casting model to perform context-aware recommendation in mobile digital assistants, which models the convoluted correlation within contextual signals and between context and intent to address sparsely and heterogeneity of contextual signals. . Government Accounting Office studied the content data on location based mostly social networks with regard to point-of-interest properties, user interests, and sentiment indications that models 3 kinds of data beneath a unified point-of-interest recommendation framework with the thought of their relationship to arrival actions. In distinction, on-line social voting's area unit quite totally different from the standard recommendation things in terms of social propagation. Totally different from the present Social-based RSs, besides social relationship, our models additionally explore user-group affiliation data. We have a tendency to study the way to improve social option recommendation victimization social network. And group information simultaneously. One-class collaborative filtering (OCCF) deals with binary rating data, reflecting a user's action or not. In OCCF, only positive samples are observed, and there are a large number of missing entries. OCCF has been widely studied. This paper can also be classified into OCCF. The difference is that we are dealing with binary data from multiple channels, consisting of binary user-voting activities, user–user trust relationships, and user-group affiliations. We are the first to study recommendation of the emerging online social voting's to the best of our knowledge. NN algorithms identify the so-called neighbors of a target user. A prediction of item preferences or a list of recommended items for the target user can be produced by combining preferences of the neighbors. Jamal and Ester

[26] proposed an approach, namely Trust-CF, to incorporate social network

3. PREVIOUS WORK

It is demonstrated that people's adoption towards voting activities is being influenced by OSNs. Collaborative filtering-based RSs gives very accurate results for recommendation depending up on the feedback data given by the users interest. As the OSNs popularity is being increased it provides pure rating-based RSs with additional information. Previously there are many studies on how a social network increases recommendation for accurate results.

Disadvantages

1) Less Accuracy.

2) It is very difficult task and a challenge to show the "right voting's" to the "right users".

3) Social voting causes new opportunities and challenges for RSs using social information.

4. PROPOSED SYSTEM

In this paper, we represent our effort on RSs development for online social voting's, i.e., by recommending voting campaigns to users for who are interested. We develop a RS model which includes neighbor (NN)-based models and matrix-factorization (MF) based models, to know the user interest in voting by mining the information on user-voting, user to user friends, and user group affliction.

We compare and evaluate the performance of the models by taking real time social voting trace. Experiments on NN-based models show that the group affiliation information dominates the social network information.

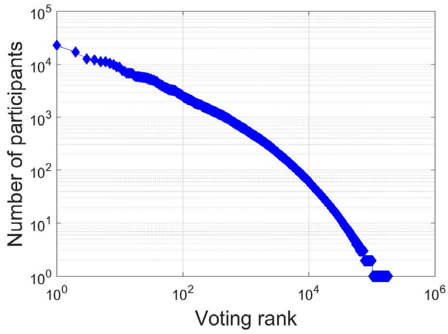
Advantages:

1. Accuracy for popularity-based voting recommendation has been increased based on OSN information and group affiliation.

2. In KNN based voting Group affiliation gets dominated by OSN.

5. IMPLEMENTATION

5.1. ADMIN



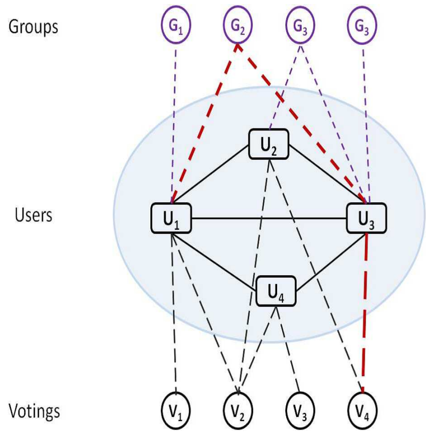
In this module, the Admin has to login by using valid user name and password. After login successful he can perform some operations such as Authorizing users, List Users and Authorize, View all Friend request and response, Add Posts, View all Posts with Videos, View All Recommended Posts, View All Service Usage Reviewed Posts, View all user search History, View Collaborative Filtering based Recommendation, Find Top K Hit Rate in chart.

5.2. FRIEND_REQUESTS RESPONSE

In this module admin can check the friends of his list and also friend requests sent to him. He can accept those friend requests by that he can improve this recommendation for a product by those friends. If he is not accepting the friend requests then they will remain like that and cannot participate in the voting process. After accepting the friend request user can participate in the elections.

5.3. SOCIAL_NETWORK_FRIENDS

Here user can see his friends those who are belonging to the same network sites. And also his details such as request form, request to user's site, user name. Some friends may be belonging to different networks they are also seen.

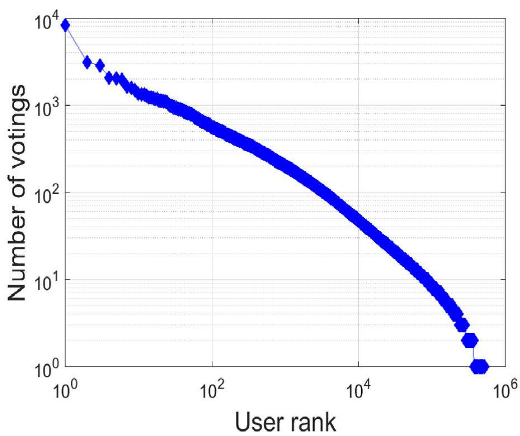


5.4. ALL_RECOMMENDED_POSTS

5.5. ADDING_POSTS

In this module, the admin adds posts details such as title, description and the image of the post. The post details such as title and description will be encrypted and stores into the database.

5.6. USER



In this module first user has to register by filling the user form. After filling the user form user gets the access to enter into the network so that he can view all the posts and also recommend any post to his friends list. And also by seeing the recommendation done to a product he can buy them. User after registering into the account with id and password he has to give the correct login id and password so that he can login. After logging in he can see some operations like search a product, view recommendation and so on.

5.7. SEARCHING USERS

In this module, the user searches for users in Same Site and in Different Sites and sends friend requests to them. The user can search for users in other sites to make friends only if they have permission.

6. CONCLUSION AND FUTURE WORK

For this project, we have downloaded the datasets from the twitter account by using hadoop cluster and also flume and hive. By using those datasets we represent a set KNN-based Recommended System for social voting. From experiments with the datasets collected from twitter, it is clear that social network information can improve the accuracy of voting based on recommendation.

This experiment can be done on facebook also but getting facebook data is not possible. Facebook does not provide the option of downloading datasets and also neighborhood has a limitation as the data set size increases the KNN decreases. This project is our first step towards the study of social voting recommendation. As an instantaneous work item in future, we'd prefer to study however option content data may be mined for recommendation, particularly for cold voting's. We tend to inquisitive about developing option RSs made-to-order for individual users, given the supply of multichannel data regarding their social neighborhoods and activities.

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