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Review on Online Social Voting based on Collaborative Filtering

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Abstract - *With the advancement of information and communication techniques, sharing information through social voting is spring up new feature in online social networks. The increasing popularity of social voting suddenly brings forth the "information overload" problem. In this paper, we conduct a comprehensive study of a set of matrix factorization (MF) and nearest-neighbor (NN) – based recommender system (RSs), which explore user social network along with group affiliation information for social voting recommendation. The MF and NN models observe that social and group information is much more valuable to cold user than to heavy users. Finding appropriate item from available set of options for nonhot voting's can be better mined by MF models. Along with MF and NN based recommendation we consider hybrid RS to achieve the best top-k hit rate.*

***Key Words*: Collaborative filtering, online social networks (OSNs), recommender systems (RSs).**

1. INTRODUCTION

Remarkable growth within the quality of online social networks(OSNs) in recent years. Most of existing online social networks like Face book & Twitter area unit designed to bias towards data speech act to an outsized audience and additionally raises variety of privacy and security problems. Though OSNs permits one user to limit access to her/his knowledge, presently they are doing not give any mechanism to enforce privacy considerations over knowledge related to multiple users. Recommender techniques are a primary a part of the information as well as ecommerce system. They represent a Powerful methodology for enabling users to filter by suggests that of large amount of information and merchandise areas.

Online Social Networks (OSN), like Facebook and Twitter, facilitate easy information sharing among friends. A user not only can share his/her updates, in forms of text, picture, and video, with her direct friends, but also can quickly disseminate those updates to a much larger audience of indirect friends, grasp on the rich connectivity and global reach of popular OSNs. Many OSNs now offer 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.

The increasing popularity of social voting immediately brings forth the "information overload" problem: a user can be easily overwhelmed by various votings that were initiated, participated, or retweeted 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. Recommender systems (RSs) look at information overload by suggesting to users the items that are potentially of their interests.

Obtaining recommendations from trusted sources is a critical component of the natural process of human decision making. Recommender Systems have evolved to fulfill the natural dual need of buyers and sellers by automating the generation of recommendations based on data analysis. The motivation was to leverage social collaboration in order to prevent users from getting inundated by a large volume of streaming documents. Collaborative filtering, which analyzes usage data across users to find well matched user-item pairs, has since been juxtaposed against the older methodology of content filtering which had its original roots in information retrieval. This lead to drawbacks. 1) Trust-CF does not work with binary data set, as the weighted average of all observed items is 1. 2) Social voting poses unique challenges and opportunities for RSs utilizing social trust information.

Due to social proliferation and social domination, a user's voting behavior is strongly correlated with him/her social friends. Social voting poses unique challenges and opportunities for RSs utilizing social trust information. Voting participation data are binary without negative samples. It is intriguing to develop RSs for social voting. Towards addressing these challenges, we introduce set of Recommend system (RS) models, matrix factorization based model and nearest neighbor (NN)-based models.

2. RELATED WORK

Xiaoyuan Su [2] proposed first introduce CF tasks and their main challenges, such as data sparsity, scalability, synonymy, gray sheep, shilling attacks, privacy protection, etc., and their possible solutions. It demonstrated three main categories of CF techniques: memory-based, model based, and hybrid CF algorithms (that combine CF with other recommendation techniques), with examples for indicative algorithms of each category, and analysis of their predictive performance and their ability to address the challenges.

Yehuda Koren [3] proposed a theory on Collaborating Filtering (CF), where past transactions were analyzed in order to establish connections between users and products. The two more successful approaches to CF were latent factor models, which directly profile both users and products, and neighborhood models, which analyze similarities between products or users. The factor and neighborhood models can be smoothly merged, thereby building a more accurate combined model.

Kimikazu Kato [4] proposed a theory on collaborative filtering, a singular value decomposition (SVD) is needed to reduce the size of a large scale matrix so that the burden for the next phase computation will be decreased. In this SVD means a roughly approximated factorization of a given matrix into smaller sized matrices. Webb (a.k.a. Simon Funk) revealed an effective algorithm to compute SVD toward a solution of an open competition called "Netflix Prize". The algorithm utilizes an iterative method so that the error of approximation improves in each step of the iteration. It gave a GPU version of Webb's algorithm.

Kai Yu [5] explored a theory on Abstract—Memory-based collaborative filtering (CF) has been studied extensively in the literature and has proven to be successful in various types of personalized recommender systems. It developed a probabilistic framework for memory-based CF (PMCF). This framework has clear links with classical memory-based CF, it allows to find principled solutions to known problems of CF-based recommender systems. In particular, it shows that a probabilistic active learning method can be used to actively query the user, thereby solving the "new user problem." Furthermore, the probabilistic framework allows reducing the computational cost of memory-based CF by working on a carefully selected subset of user profiles, while retaining high accuracy.

Paolo Cremonesi [6] proposed that most commercial systems, the 'best bet' recommendations were shown, but the predicted rating values are not. It was usually referred to as a top-N recommendation task, where the goal of the recommender system is to find a few specific items which were supposed to be most appealing to the user. Common methodologies based on error metrics (such as RMSE) are not a natural fit for calculating the top-N recommendation task. Preferably, top-N performance can be directly measured by alternative methodologies based on accuracy metrics (such as precision/recall).

Yang Guo [7] proposed a theory on comprehensive study on improving the accuracy of top-k recommendation using social networks. It first showed that the existing social-trust enhanced Matrix Factorization (MF) models can be tailored for top-k recommendation by including observed and missing ratings in their training objective functions. He also proposed a Nearest Neighbor (NN) based top-k recommendation method that combines users neighborhoods in the trust network with their neighborhoods in the latent feature space.

Philip S. Yu [8] proposed a theory on similarity search that was defined among the same type of objects in heterogeneous networks. Moreover, different linkage paths are considered in a network, one could derive various similarity semantics. Therefore, it also introduces the concept of meta path-based similarity, where a meta path was a path consisting of a sequence of relations defined between different object types. Under the meta path framework it defined a novel similarity measure called PathSim that is able to find peer objects in the network (e.g., find authors in the similar field and with similar reputation), which turns out to be more meaningful in many scenarios compared with random-walk based similarity measures.

Brandon Norick [9] proposed that to integrate meta-path selection with user-guided clustering to cluster objects in networks, where a user first provides a small set of object seeds for each cluster as guidance. Then the weights were learn the system for each meta-path that are consistent with the clustering result implied by the guidance, and generates clusters under the learned weights of meta-paths.

3. PROPOSED SYSTEM

In existing system Social voting as a new social network application has not been studied much. The motive of starting a voting is to engage people to manifest their opinions. Compared with existing items for recommendation, the uniqueness of online social voting lays in its social propagation along social links. As shown in Fig 1. [1] any user can initiate the a voting paradigm. After voting start off, there are two major ways through which other users can see the voting and potentially participate.

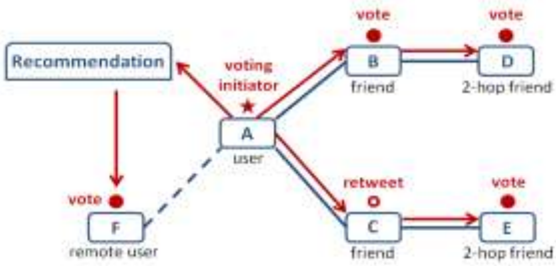

Fig -1: Social voting propagation paradigm

1) Social Propagation: - After a user start off or take part into a voting, all his/her followers can see the voting; a user can also choose only retweet a voting to his followers without participation.

2) Weibo Voting Recommendation List: - In this approach popular voting's and personalized recommendation are consider [10].

3.1 SOCIAL VOTING RECOMMENDATION

In OSNs system top-k voting recommendation is consider. For every user, the RS has to recommend a small number, let k, of votings from all available votings.

A. MATRIX FACTERIZATION

Matrix is used to represent social network information. MF will helps to non-social people. The voting system requires social relationship in nearest neighbor (NN) (u->v). Here matrix factorization (MF) does not require any social relationship. Calculate hot voting is main motive of this concept without social relationship.

In MF we rank the voting according to user-voting interaction $R_{u,i,}$ as calculating the predicted rating of user u on voting i:

$$R_{u,i} = r_m + Q_u P_i^T \quad (1)$$

In eq. (1) $R_{u,i}$ is the user-voting interaction [1], r_m is the user voting interaction of target vote latent feature, $Q_u P_i^T$ is score of voting interaction. With this social network information is carried out in model training.

B. Nearest – Neighbor (NN)

In this metapath is used to construct Nearest – Neighborhoods for the target users with the four format as 1) U-G-U-V metapath: Counting of P_i Voting latent Feature of v (target user) of group's of user u (vote initiator) 2) U-U-V metapath: Voting count of U's followers/friends with in m-hops with some latent features. In this 1-hop is considered as direct friend, 2-hop is consider as indirect friend. 3) U-V-U-V metapath: In this metapath, finds the set of users who have participated. Take count of the voting's participated vote initiator's previous votings. 4) UNN: Other than these neighborhoods visited through metapaths, we also explore neighborhoods in the user latent feature space derived from MF models. Set of NNs of user u in the user latent feature space, and the NN of user u are weighted according to their similarity sim(u,v) with user u. Simply take U's latent feature and count the voting participated of LF. Three types of objects namely, user (U), voting (V) and group (G).

C. HYBRID APPROACH

The combined neighborhoods are taken into consideration. Hybrid approach is combination of UGUV, UUV (m-hop), UVUV, and UNN approaches. Hybrid approach is calculated using score of a potential relevant voting I for user u.

4. CONCLUSION

This paper proposes a set of MF – based and NN – based RSs for online social voting. System signifies social network information and group information is much more valuable to recommendation accuracy for cold users than for heavy users. The result was evaluated based on standard dataset.

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