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A NOVEL RECOMMENDATION MODEL REGULARIZED WITH USER TRUST AND ITEM RATINGS

S.Siamala Devi[1], .N.Kokila[2], M.Nagamuthulakshmi[3], R.Priya[4]

[1]Assistant Professor,Department of Computer Science and Engineering,Sri Krishna College of Technology, Coimbatore

[2,3,4]UG Scholar,Department of Computer Science and Engineering,Sri Krishna College of Technology, Coimbatore

Abstract:Singular Value Decomposition (SVD) is a trust-based matrix factorization technique for recommendations is proposed. Trust SVD integrates multiple information sources into the recommendation model to reduce the data sparsity and cold start problems and their deterioration of recommendation performance. An analysis of social trust data from four real-world data sets suggests that both the explicit and the implicit influence of both ratings and trust should be taken into consideration in a recommendation model. Trust SVD therefore builds on top of a state-of-the-art recommendation algorithm, SVD++ uses the explicit and implicit influence of rated items, by further incorporating both the explicit and implicit influence of trusted and trusting users on the guess of items for an active user. The proposed technique extends SVD++ with social trust information. Experimental results on the four data sets demonstrate that Trust SVD achieves accuracy than other recommendation techniques.

Keywords: **Data Mining, Recommender systems, Rating prediction, Explicit and Implicit influence.**

I. INTRODUCTION

A Novel trust-based recommendation model, which is regularized with user trust and item rating is Trust SVD. Our method is novel for its consideration of both the explicit (rating based on social circle) and implicit influence (self-rating) of item ratings and of the user trust. In addition, a weighted regularization technique is used to avoid over-fitting for model learning. This trust-based matrix factorization model incorporates both rating and trust information for rating prediction.Trust information is very sparse, yet complementary to the information. Thus, focusing too much on either one kind of information achieves only marginal gains in predictive correctness. 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 are 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 regularize the user- and item specific latent feature vectors. This guarantees that the user-specific vectors can be learned from their trust information even if a few or no ratings are given. So data sparsity and cold start issues for recommendation can be solved. TrustSVD can outperform both trust and ratings based methods in the predictive accuracy.Recommender systems employ from a specific type of information filtering system technique that attempts to recommend information items (movies, TV program/show/episode, video on demand,web pages, books, news, music,images, scientific literature etc.) or social elements (e.g. people, events or groups) that are likely to be of interest to the user. Typically, a recommender system approximates a user profile to some reference characteristics, and tries to predict the 'rating' or 'preference' that a user would give to an item. These characteristics may be from the information item which may be similar (the content-based approach) or the user's social surrounding (the collaborative filtering). The recommender system applies Data Mining (DM) approaches and prediction algorithms to predict user’s interest on facts, product and services. However, most of these systems can bear in their core an algorithm that can be used to understand a particular case of a Data Mining (DM) technique. The process of data mining consists of 3 steps: Data Preprocessing, Data Analysis and Result Interpretation. Examples of recommender system are amazon.com, eBay, snapdeal.com

II. BACKGROUND

Recommender systems produce a list of recommendations through collaborative or content-based filtering. Content based algorithm recommender system are the recommender system which work with profiles of users that are created at the start. A profile has information about a user and his/her taste. Taste is based on how the user has rated the items.

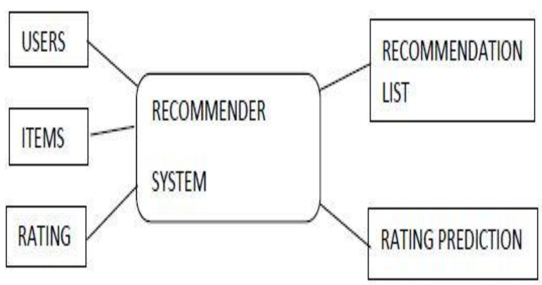


Figure 1 Recommender System

Collaborative filtering Algorithm is a type of recommender system became one of the most researched techniques in the recommender systems since this approach was described by Paul Resnick and Hal Varian in 1997. [1] The idea of collaborative filtering is, finding users in a community that shares appreciations. If two users have same or almost same rated items in common, then they have similar tastes [2]. Such users build a group or a so calledneighborhood. A user gets recommendations to the items that he/she has not rated before, but that were already positively rated by users in his/her neighborhood. Several approaches of collaborative filtering are (1) User based approach(2) Item based approach,

2.1 User based approach: In this approach, the users perform the main role. If definite majority of the customers has the same taste, then they join into one group. Recommendations are given to the user based on the evaluation of items by other users. If the item was positively rated by the community, it will be recommended to the user.

2.2 Item Based Approach: The taste of users remains constant or changes very slightly the similar items build neighborhoods based on the appreciations of the users. Afterwards, the system creates recommendations with items in the neighborhood that a user would choose.

III. LITERATURE SURVEY

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

1. P. Massa and P. Avesani [13] proposes a Trust-aware Recommender System. Recommender Systems based on Collaborative Filtering suggest user's items they might like. Although due to the data sparsity of input ratings matrix, the pace of finding similar users often fails. This paper propose to replace it with the use of a trust metric, an algorithm able to generate trust over trust network. It also evaluates a trust weight that can be used in place similarity weight. In the first step we find the neighbors and in second step system predicts ratings based on a weighted sum of ratings given by neighbors to items. The weight can be derived from the user similarity assessment or with use of a trust metric. The results specify that trust is very effective in solving RSs weaknesses.

2. M. Jamali and M. Ester [14] explores a Model-based approach for recommendation in social networks, which uses a matrix factorization technique. The dormant characteristics of users and items are absorbed 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 labels the transitivity of trust in social network by considering the trust propagation in the network. Because social influence behavior of a user is influenced 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 absorbed as long as he/she is connected to the social network via a social relation. Thus SocialMF deals better with cold start users than existing methods.

3. H. Fang, Y. Bao, and J. Zhang [12] 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 or similarity and to acquire trust information more effectively. By degrading the explicit trust values to finer-grained trust aspects, we can derive more effective information for recommendation. In this paper they discovered four general features of trust (i.e. benevolence,

competence, integrity and predictability) and modeled them based on users' past ratings. The four features 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 got from the SVR model and by measuring resemblances between the corresponding latent feature vectors factorized from rating matrix of the user. Thus, we can re-explain the trust value for the recommendation, and surely can update user's dormant feature vector by considering social influence of other users trusting and being trusted by the user.

4. X. Yang, H. Steck, and Y. Liu [6] 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 match to particular item lists 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 theorize the trust value on each link based on user rating activities in each list. To deduce 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.

IV. EXISTING SYSTEM

Many approaches have been suggested in this field, including both memory- and model-based methods.

1. Golbeck proposes a TidalTrust[3] approach to aggregate the ratings of trusted neighbors for a rating prediction, where trust is figured in a breadth-first manner.
2. Guo et al. produced a user's rating profile[4]

by merging those of trusted users through which better recommendations can be created and the cold start and data sparsity issues can be handled better. However, memory-based approaches have difficulty in adapting to large-scale data sets, and are often time-consuming to find candidate neighbors in a large user area.

3. Zhu et al. propose a graph Laplacian regularizer[5] to capture the potentially social relationships among users, and form the social recommendation issue as a low rank semi-definite problem. Although, empirical evaluation indicates that very marginal improvements are obtained in comparison with the RSTE model.
4. Yang et al. propose a hybrid method TrustMF [6] that combines both a truster model and a trustee model from the perspectives of trusters and trustees, that is, both the users who trust the active user and those who are trusted by the user will impact the user's ratings on unknown items.

V. DISADVANTAGES OF EXISTING SYSTEM

Existing trust-based models may not work well if there prevails only trust-alike relationships.

a. These observations could other kinds of recommendation problems.
b. Existing trust based models judges the explicit influence of ratings.
c. The utility of ratings is not well exploited.
d. Existing trust-based models do not consider the explicit and implicit influence of trust simultaneously.

VI. PROBLEM DEFINITION

The reason to define the algorithm for predicting the users interest instead of existing algorithms are

a. Collaborative Filtering suffers from two well

known issues are data sparsity and cold start.

b. Unsuitable for real life applications because of the increased computational and communication costs.

Some other problems are:

1. *Cold start*: It's difficult to give recommendations to new users as his/her profile is almost empty and he has not rated any items yet so his taste is unknown to the system. This is called the cold start problem. In some recommender systems this problem is solved with observationwhen creating a profile. Items may also have a cold-start when they are fresh in the system and haven't been rated before. Both of these problems can be also solved with hybrid approaches. [1]

2. *Trust*: The voices of people with a short history may not be that relevant as the voices of those who have rich history in their profiles. The issue of trust arises towards evaluations of a definite customer. The issue could be solved by distribution of preferencesto the users. [1]

3. *Scalability*: With the growth of numbers of users and items, the system requires more resources for processing information and forming recommendations. Most of resources is consumed with the purpose of determining users with similar tastes, and goods with similar descriptions. This problem can also be cleared by the combination of several types of filters and physical enhancement of systems. Parts of numerous computations may also be implemented offline in order to accelerate issuance of recommendations online. [1]

4. *Sparsity*: In online shopping those have a huge amount of users and items there are almost always users that have rated just a few items. Using collaborative filtering and other approaches recommender systems generally create neighborhoods of users using their profiles. If a user has evaluated just few items then it's pretty difficult to determine his/her taste and he/she could be related to the wrong neighborhood. Sparsity is the problem of lack of information. [1]

5. *Privacy*: Privacy has been the most important problem. In order to obtain the most accurate and exact recommendation, the system must gain the most amount of information possible about the user, including demographic data, and data about the location of a particular user. Automatically, the question of reliability, security and confidentiality of the given information arises. Many online shops offer effective protection of privacy of the users by utilizing specialized algorithms and programs.[1]

VII. NEED FOR RECOMMENDATION SYSTEMS

1. *Domain* – Recommendation systems has its importance in various areas and with the regard of internet, the number is still growing. Based on the research carried out, most of the articles were related to Movie recommendations (46 out of 164 articles) owing to easy availability of the movies dataset Movie Lens. The second most sought after domain is E-commerce (33 out of 164 articles). Although, a huge volume of recommendation systems literature is focused on varied topics such as Entertainment and Beyond e.g., Social Media e.g., Suggesting Friends, Face Recognition for picture tags; Match Making; Tourism e.g. tripadvisor.com; e-news; digital library, Books, Music , Mobile App downloads.

2. *Purpose* –The compelling reason for effecting recommendations in E-commerce is that they have become serious business tools to inflate the sales by improving cross-sell by suggesting additional products and gaining customer loyalty resulting in repeat business.

3. *Recommendation Context* –It refers to the context in which the recommendation is being made. It answers the question - What the user is doing when the recommendation is made. E.g. hanging out with friends, looking for an eating joint in a user's nearby location. Recommendation systems that consider set of users as input to these system, are starting to elaborate and are used in different areas likemusic, tourism, web etc. Currently, mobile applications use GPS feature to fetch the current geographic location of user, and employ recommender systems to use this information for creating recommendations e.g., Jin-Hyuk Hong , Zomato app. Moon-Hee Park , SungBae Cho (2007) proposed to model user preference in restaurants by using context-aware facts and user profile by applying map-based Personalized Recommendations using Bayesian Network.

4. *Who's Opinion* – It refers to people on whose opinions, recommendations are made e.g., Friends, Friends of Friend, Experts. SRS uses User's trust network which is the social levels - Recommendations have many variants. They could be in the form of Non-personalized abstract stats (e.g.,Popular movies, Best Seller books), Demographic personalization based on target set (e.g., Male/female, different age groups), Transient personalization based on current direction (e.g., item generally brought with another item – Product related recommendation), Sustenance personalization based on preferences and behavior (e.g., based on combination of user's old purchases, his rating for products and his browsing history).

5. *Privacy and Trustworthiness* –Seclusion is an important issue because these systems exploit information from social networking sites which has a lot of information about its registered users. How much of the user's personal data to be revealed? For privacy preservation, a certain level of ambiguity must be introduced into the predictions. A tradeoff must be maintained between the accuracy and predictions.

VIII. PROPOSED SYSTEM

We suggest a novel trust-based recommendation model regularized with user trust and item ratings, known as TrustSVD.

Our approach builds on top of a state-of-the-art model SVD++ through which the explicit and implicit influence of user-item ratings are involved to produce predictions. In addition, we further consider the influence of trust users (including trustees and trusters) on the rating guesses for an active user.

This ensures that user specific vectors can be learned from their trust information even if a few or no ratings are given. So the concerned issues can be alleviated.

Thus, explicit and implicit influences of item ratings and user trust have been considered in our model, indicating its novelty. Including a weighted-regularization technique is used to avoid over-fitting for model learning.

The experimental results on the data sets demonstrate that our approach works better than other trust-based counterparts as well as other ratings-only high-performing models in terms of predictive correctness, and is more capable of surviving the cold-start situations.

There are two recommendation tasks in recommender systems, specifically item recommendation and rating prediction. Most algorithmic approaches are best designed for either one of the recommendations tasks, and this work focus on the rating prediction task.

The trust-alike relationships as the social relationships that are similar with, but weaker (or more noisy) than social trust is defined. The similarities are that both kinds of relationships indicate user preferences to some extent and thus useful for recommender systems, while the differences are that trust-alike relationships are often weaker in strength and likely to be noisier.

Typical examples are friendship and membership for recommender systems. Although these relationships also indicate that users may have a positive correlation with user similarity, there is no guarantee that such a positive evaluation always exists and that the correlation will be strong. It is well recognized that friendship can be built based on offline relations, such as colleagues and classmates, which does not necessarily share similar preferences.

Trust is a complex concept with a number of properties, such as asymmetry and domain dependence, which trust-alike relationships may not hold, e.g., friendship is undirected and domain independent. For clarity, in this article we refer trust users or trust neighbors to as the union set of users who trust an active user (i.e., trusters) and of users who are trusted by the active user (i.e., trustees).

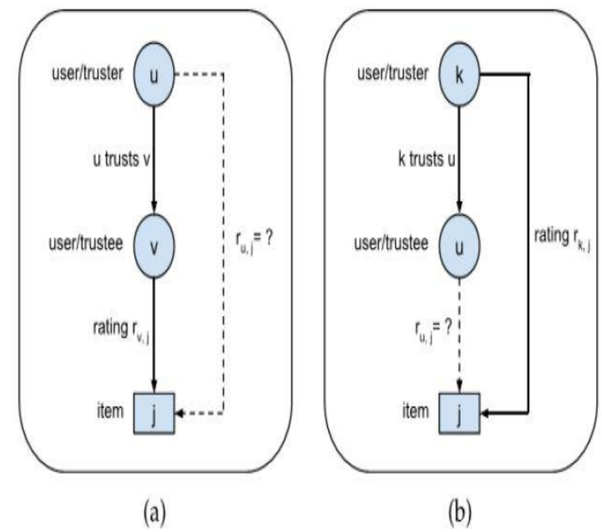


Figure 2: The influence of (a) Trustees v and (b) Trusters k on the rating prediction for the active user u and target item j.

IX. ADVANTAGES OF PROPOSED SYSTEM

Our first contribution is to conduct an empirical trust analysis and observe that trust and ratings can complement to each other, and that users may be strongly or weakly correlated with each other according to different types of social relationships.

These observations motivate us to consider both explicit and implicit influence of ratings and trust into our trust-based model.

Potentially, these observations could be also beneficial for solving other kinds of recommendation problems, e.g., top-N item recommendation.

X. RECOMMENDATION TECHNIQUES USED

CONTENT-BASED FILTERING TECHNIQUES:

For point of interest recommender systems are personalized by mining user preferences in [11] to understand user preferences transition patterns to improve accuracy of POI recommendation systems but users textual comments are not considered for making predictions. This paper helps study users preference transition across categories of point of interest and further predictions are done based on this analysis.

MATRIX FACTORIZATION TECHNIQUES:

Research on matrix factorization techniques done in [7] shows how they are better than classic nearest neighbor technique. It shows us matrix factorization model that incorporates implicit feedback, confidence levels and temporal effects.

MATRIX FACTORIZATION USING USER TRUST INFORMATION:

User trust applied to social collaborative filtering techniques in [8] show how trust based social collaborative filtering techniques work well in case of cold start and integrates item ratings and user trust to improve predictive accuracy but it is inferior to latest state of the art ratings only model. It creates hybrid model by integrating item rating with user trust based on truster and trustee model to compute influence on item ratings.

Probabilistic matrix factorization is used with social recommendation in [9] to demonstrate how social recommendations can be scalable to even very large datasets as it scales linearly with number of observations. In case of few or no ratings, this system performs better than other state of the art systems but distrust information is not accounted for in this system. Problems of poor prediction accuracy and data sparsity are solved by employed rating records and user social network information.

Recommender systems with social regularization [10] provide solution which is generic and easily extensible but it may have adverse impact in case of some social connections. It shows ways wherein recommendation systems are benefitted by social trust.

Better quality trust information is derived by using decomposed trust in matrix factorization [12], but they do not consider trust transitivity of the trust networks. Trust information is able to explain user similarity only up to some extent. This information can be combined with truster and trustee information to improve prediction accuracy.

XI. METHODOLOGY

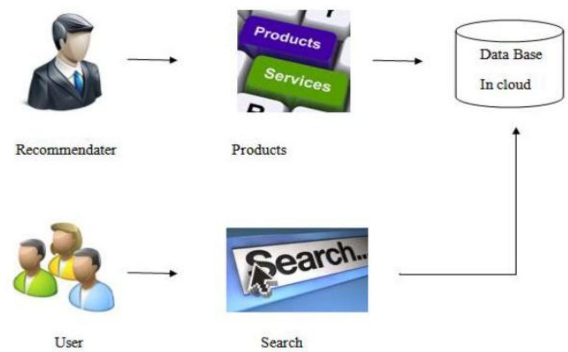
1. *Linear combination*: A straightforward way to linearly combine the two kinds of implicit trust influence. It means that the influence of trusting users is considered; indicates that the influence of trusted users are considered; and combines the two kinds of trust influence together.
2. *All as trusting users*: In a trust relationship, a

user u can be represented either by truster or trustee. Another way is to model the impact of users trust neighbors, including both trusted and trusting users, in the manner of trusting users.

3. *All as trusted users*: With the same

assumption, the influence of all trust neighbors in the manner of trusted users may be designed. However, since user-feature matrix P plays a key role in bridging both rating and trust information, the rating prediction.

XII. SYSTEM ARCHITECTURE



XIII. CONCLUSION

A novel trust-based matrix factorization model which incorporated both rating and trust information is proposed. The analysis of trust in four real-world data sets indicated that trust and ratings were complementary to each other, and both pivotal for more accurate recommendations. This novel approach, trust SVD, takes into account both the explicit and implicit influence of ratings and of trust information when predicting ratings of unknown items. Both the trust influence of trustees and trusters of active users are involved in this model. As a rating prediction model, trust SVD works well by incorporating trust influence. However, the literature has shown that models for rating prediction cannot suit the task of top-N item recommendation. For future work, an idea will be introduced by which trust can influence the ranking score of an item (both explicitly and implicitly) can be studied. The ranking order between a rated item and an unrated item (but rated by trust users) may be critical to learn user ranking patterns.

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