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A DIFFERENT PROPOSAL MODEL CONSISTENT WITH USER TRUST AND ITEM RATINGS

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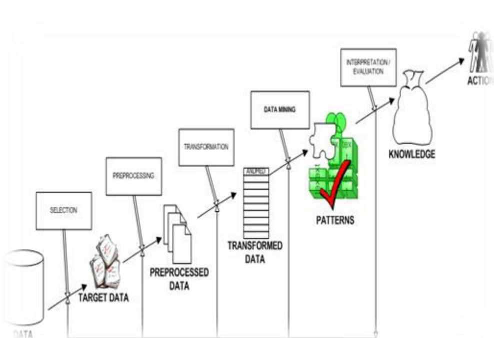
ABSTRACT

We propose TrustSVD, a trust-based matrix factorization technique for recommendations. TrustSVD integrates multiple information sources into the recommendation model in order to reduce the data sparsity and cold start problems and their degradation of recommendation performance. An analysis of social trust data from four real-world data sets suggests that not only the explicit but also the implicit influence of both ratings and trust should be taken into consideration in a recommendation model. TrustSVD therefore builds on top of a state-of-the-art recommendation algorithm, SVD++ (which 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 prediction of items for an active user. The proposed technique is the first to extend SVD++ with social trust information. Experimental results on the four data sets demonstrate that TrustSVD achieves better accuracy than other ten counterparts recommendation techniques

I.INTRODUCTION

What is Data Mining?



Structure of Data Mining

Generally, data mining (sometimes called data or knowledge discovery) is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cuts costs, or both. Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and

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summarize the relationships identified. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases.

How Data Mining Works?

While large-scale information technology has been evolving separate transaction and analytical systems, data mining provides the link between the two. Data mining software analyzes relationships and patterns in stored transaction data based on open-ended user queries. Several types of analytical software are available: statistical, machine learning, and neural networks.

Generally, any of four types of relationships are sought:

- **Classes**: Stored data is used to locate data in predetermined groups. For example, a restaurant chain could mine customer purchase data to determine when customers visit and what they typically order. This information could be used to increase traffic by having daily specials.
- **Clusters**: Data items are grouped according to logical relationships or consumer preferences. For example, data can be mined to identify market segments or consumer affinities.
- **Associations**: Data can be mined to identify associations. The beer-diaper example is an example of associative mining.
- **Sequential patterns**: Data is mined to anticipate behavior patterns and trends. For example, an outdoor equipment retailer could predict the likelihood of a backpack being purchased based on a consumer's purchase of sleeping bags and hiking shoes.

Data mining consists of five major elements:

1) Extract, transform, and load transaction data onto the data warehouse system.
2) Store and manage the data in a multidimensional database system.
3) Provide data access to business analysts and information technology professionals.
4) Analyze the data by application software.
5) Present the data in a useful format, such as a graph or table.

Different levels of analysis are available:

- **Artificial neural networks**: Non-linear predictive models that learn through training and resemble biological neural networks in structure.

- **Genetic algorithms**: Optimization techniques that use process such as genetic combination, mutation, and natural selection in a design based on the concepts of natural evolution.

- **Decision trees**: Tree-shaped structures that represent sets of decisions. These decisions generate

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rules for the classification of a dataset. Specific decision tree methods include Classification and Regression Trees (CART) and Chi Square Automatic Interaction Detection (CHAID). CART and CHAID are decision tree techniques used for classification of a dataset. They provide a set of rules that you can apply to a new (unclassified) dataset to predict which records will have a given outcome. CART segments a dataset by creating 2-way splits while CHAID segments using chi square tests to create multi-way splits. CART typically requires less data preparation than CHAID.

- **Nearest neighbor method**: A technique that classifies each record in a dataset based on a combination of the classes of the *k* record(s) most similar to it in a historical dataset (where *k*=1). Sometimes called the *k*-nearest neighbor technique.

- **Rule induction**: The extraction of useful if-then rules from data based on statistical significance.

- **Data visualization**: The visual interpretation of complex relationships in multidimensional data. Graphics tools are used to illustrate data relationships.

Characteristics of Data Mining:

- **Large quantities of data**: The volume of data so great it has to be analyzed by automated techniques e.g. satellite information, credit card transactions etc.
- **Noisy, incomplete data**: Imprecise data is the characteristic of all data collection.
- **Complex data structure**: conventional statistical analysis not possible
- **Heterogeneous data stored in legacy systems**

Benefits of Data Mining:

1) It's one of the most effective services that are available today. With the help of data mining, one can discover precious information about the customers and their behavior for a specific set of products and evaluate and analyze, store, mine and load data related to them
2) An analytical CRM model and strategic business related decisions can be made with the help of data mining as it helps in providing a complete synopsis of customers
3) An endless number of organizations have installed data mining projects and it has helped them see their own companies make an unprecedented improvement in their marketing strategies (Campaigns)
4) Data mining is generally used by organizations with a solid customer focus. For its flexible nature as far as

applicability is concerned is being used vehemently in applications to foresee crucial data including industry analysis and consumer buying behaviors

5) Fast paced and prompt access to data along with economic processing techniques have made data mining one of the most suitable services that a company seek

Advantages of Data Mining:

1. Marketing / Retail:

Data mining helps marketing companies build models based on historical data to predict who will respond to the new marketing campaigns such as direct mail, online marketing campaign…etc. Through the results, marketers will have appropriate approach to sell profitable products to targeted customers.Data mining brings a lot of benefits to retail companies in the same way as marketing. Through market basket analysis, a store can have an appropriate production arrangement in a way that customers can buy frequent buying products together with pleasant. In addition, it also helps the retail companies offer certain discounts for particular products that will attract more customers.

2. Finance / Banking

Data mining gives financial institutions information about loan information and credit reporting. By building a model from historical customer's data, the bank and financial institution can determine good and bad loans. In addition, data mining helps banks detect fraudulent credit card transactions to protect credit card's owner.

3. Manufacturing

By applying data mining in operational engineering data, manufacturers can detect faulty equipments and determine optimal control parameters. For example semi-conductor manufacturers has a challenge that even the conditions of manufacturing environments at different wafer production plants are similar, the quality of wafer are lot the same and some for unknown reasons even has defects. Data mining has been applying to determine the ranges of control parameters that lead to the production of golden wafer. Then those optimal control parameters are used to manufacture wafers with desired quality.

4. Governments

Data mining helps government agency by digging and analyzing records of financial transaction to build patterns that can detect money laundering or criminal activities.

5. Law enforcement:

Data mining can aid law enforcers in identifying criminal suspects as well as apprehending these criminals by examining trends in location, crime type, habit, and other patterns of behaviors.

6. Researchers:

Data mining can assist researchers by speeding up their data analyzing process; thus, allowing those more time to work on other projects.

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II.SYSTEM ARCHITECTURE

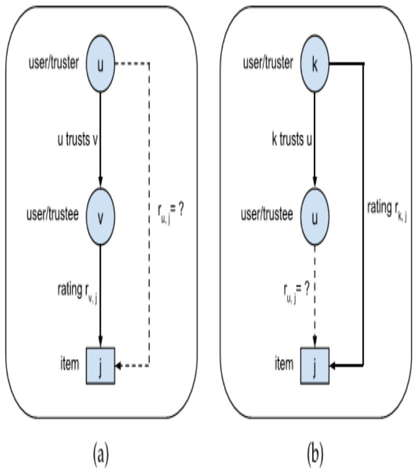

Fig. The influence of (a) trustees v and (b) trusters k on the rating prediction for the active user u and target item j.

III.EXISTING SYSTEM

Collaborative filtering (CF) is one of the most popular techniques to implement a recommender system. The idea of CF is that users with similar preferences in the past are likely to favor the same items (e.g., movies, music, books, etc.) in the future. CF has also been applied to tasks besides item recommendations, in domains such as image processing and bioinformatics. However, CF suffers from two well known issues: data sparsity and cold start. The former issue refers to the fact that users usually rate only a small portion of items, while the latter indicates that new users only give a few ratings (a.k.a. cold-start users). Both issues severely degrade the efficiency of a recommender system in modeling user preferences and thus the accuracy of predicting a user's rating for an unknown item. To help resolve these issues, many researchers attempt to incorporate social trust information into their recommendation models, given that model-based CF approaches outperform memory-based approaches. These approaches further regularize the user-specific feature vectors by the phenomenon that friends often influence each other in recommending items. However, even the best performance reported by the latest work can be inferior to that of other state-of-the-art models which are merely based on user–item ratings. For instance, a well-performing trust-based model obtains 1.0585 on data set Epinions. com in terms of Root Mean Square Error (RMSE), whereas the performance of a user–item baseline (see, Koren, Section 2.1) can achieve 1.0472 in terms of RMSE.

Disadvantages:

1. CF suffers from two well known issues are data sparsity and cold start.

IV.PROPOSED SYSTEM

We propose a novel trust-based recommendation model regularized with user trust and item ratings, termed Trust SVD. Our approach builds on top of a state-of the-art model SVD++ through which both the explicit and implicit influence of user–item ratings are involved to generate predictions. In addition, we further consider the influence of user trust (including trustees and trusters) on the rating prediction for an active user. To the authors' knowledge, our work is the first to extend SVD++ with

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social trust information. Specifically, on one hand the implicit influence of trust (who trusts whom) can be naturally added to the SVD++ model by extending the user modeling. On the other hand, the explicit influence of trust (trust values) is used to constrain that user-specific vectors should conform to their social trust relationships. This ensures that user-specific vectors can be learned from their trust information even if a few or no ratings are given. In this way, the concerned issues can be better alleviated. Our method is novel for its consideration of both the explicit and implicit influence of item ratings and of user trust. In addition, a weighted-regularization technique is used to help avoid over-fitting for model learning.

Advantages

1. In high-performing ratings-only models in terms of predictive accuracy, and is more capable of coping with the cold-start situations.
2. To propose a novel trust based recommendation approach (TrustSVD2) that incorporates both (explicit and implicit) influence of rating and trust information.

V.IMPLEMENTATION

MODULES:

- System Construction
- Rating Prediction
- Item Recommendation
- A Trust-Based Recommendation Model

MODULES DESCSRIPTION:

System Construction

- In the first module, we construct social rating based system construction module for the implementation of our proposed model. In this module we design to have widely used to provide users with high-quality personalized recommendations from a large volume of choices. Robust and accurate recommendations are important in e-commerce operations (e.g., navigating product offerings, personalization, improving customer satisfaction), and in marketing (e.g.,tailored advertising, segmentation, cross-selling). In this system we focus on user-item ratings, Item Rating Prediction, user can recommend a item to their friends.
- In this module, we develop the basic features of Online Social Networking system module. We build up the system with the feature of Online Social Networking. Where, this module is used for new user registrations and after registrations the users can login with their authentication.
- Where users can also share post with others. The user can able to search the other user profiles and public posts. In this module users can also accept and send friend requests.

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- With all the basic feature of Online Social Networking System modules is build up in the initial module, to prove and evaluate our system features. In addition we develop this module by that the users can provide the Ratings.

Rating Prediction

- In this module, we develop the option of providing the Rating by the Social User. In this Rating Prediction a user can rating the items it shows in star based model. The interactions of group memberships determine if a user will connect with another user (i.e.,link prediction) or be interested in a target item. However, the empirical results show that this model is better at link prediction than rating prediction.
- The most popular and widely studied recommendation models are matrix factorization based models which aim to factorize the user item rating matrix into two low-rank user-feature and item feature matrices. Then the predictions can be generated by the inner products of user- and item-specific latent feature vectors.
- Although a user's rating to a certain item is mainly determined by the intrinsic attributes (or properties, features) of the item in question and how she appreciates these features, some extrinsic attributes may also have a non-negligible influence on the user's ratings. In this work, we focus on the influence of social trust in rating prediction, i.e., the influence of trust neighbors on an active user's rating for a specific item, a.k.a. social influence.

Item Recommendation

- In this module, we develop the Item Recommendation. Generally, in social rating networks a user can label (add) other users as trusted friends and thus form a social network. Trust is not symmetric; for example, users u1 trusts u3 but u3 does not specify user u1 as trustworthy. Besides, users can rate a set of items using a number of rating values, e.g., integers from 1 to 5. These items could be products, movies, music, etc. of interest.
- The recommendation problem in this work is to predict the rating that a user will give to an unknown item, for example, the value that user u3 will give to item i3, based on both a user-item rating matrix and a user trust matrix. Other well-recognized recommendation problems include for example top-N item recommendation.

A Trust-Based Recommendation Model

- In this module first mathematically define the recommendation problem

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in social rating networks, and then introduce the TrustSVD model.

- In the cold-start situations where users may have only rated a few items, the decomposition of trust matrix can help to learn more reliable user-specific latent feature vectors than ratings-only matrix factorization. In the extreme case where there are no ratings at all for some users, ensures that the user-specific vector can be trained and learned from the trust matrix. In this regard, incorporating trust in a matrix factorization model can alleviate the cold start problem. By considering both explicit and implicit influence of trust rather than either one, our model can better utilize trust to further mitigate the data sparsity and cold start issues.

VI.CONCLUSION

This article proposed a novel trust-based matrix factorization model which incorporated both rating and trust information. Our 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. Our novel approach, TrustSVD, 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 our model. In addition, a weighted regularization technique is adapted and employed to further regularize the generation of user- and item-specific latent feature vectors. Computational complexity of TrustSVD indicated its capability of scaling up to large-scale data sets. Comprehensive experimental results on the four real-world data sets showed that our approach TrustSVD outperformed both trust- and ratings-based methods (ten models in total) in predictive accuracy across different testing views and across users with different trust degrees. We concluded that our approach can better alleviate the data sparsity and cold start problems of recommender systems.As a rating prediction model, TrustSVD 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, we intend to study how trust can influence the ranking score of an item (both explicitly and implicitly). The ranking order between a rated item and an unrated item (but rated by trust users) may be critical to learn users' ranking patterns.

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