

SOCIAL INFLUENCE BASED PERSONAL LATENT FACTORS LEARNING FOR EFFECTIVE RECOMMENDATION

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ABSTRACT

We propose Trust SVD, a trust-based matrix factorization technique for recommendations. Trust SVD integrates multiple information sources into the recommendation model in order to reduce the data 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. Trust SVD 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 Trust SVD achieves better accuracy than other ten counterparts recommendation techniques. In this project, we propose Trust SVD, a trust-based matrix factorization technique for recommendations. Trust SVD integrates multiple information sources into the recommendation model in order to reduce the data 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. Trust SVD 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.

Keywords: Social Recommendation, Matrix Factorization, Indirect Social Relations, Latent Factor.

1. INTRODUCTION

AS an indispensable information filtering technique, recommendation system is nowadays ubiquitous in various domains, such as the recommendation of Amazon, books/movies/music at Durban, research articles on Cite Like, etc. It provides personalized recommendation and improves the user experience. In decade, the collaborative filtering methods based on matrix factorization (MF).gain popularity and become the standard model for recommendation . Factorizes user-item preference matrix to find the latent user and item factors and complete original incomplete preference matrix by multiplying these two latent factors. Though a lot of MF-based recommendation methods have been proposed and lead promising results, they suffer from data sparsely and perform poorly on cold-start who have no or few past behavior data. The booming online social networking website like Twitter, offer opportunities to overcome these weaknesses. As social relation theories, indicate, the interest of each user may be similar to or influenced by her/his friends, thus, social relations provide the extra information about users. Recent researchers have demonstrated that recommendation models with the aid of social can achieve higher prediction accuracy and provide better recommendation result. These methods can be roughly divided into two categories according to the usage of social relations. One employs the explicit and observed connections between users, which are called the direct social relation. The other indirect social relation which are the connections between users who have similar interests with other users in the same social group although they may not directly connect.

1.1 Preliminaries Related Work

The traditional recommendation systems only focus on information between users and items, where there are n users and m items. $R = [R_{ij}]_{n \times m}$ indicates the user-item rating matrix where the observed element R_{ij} records the corresponding rating value if the j -th item is rated by the i -th user, otherwise, $R_{ij} = 0$ (empty value) which needs predicting. In social recommendation, there is an extra social network defined by a matrix $S [S_{ik}]_{n \times n}$, where each component S_{ik} denotes the existence of a social relation between user i and user k . Given a user i and an item j for which R_{ij} is unknown, the task of social recommender is to predict the rating for user i on item j using both R and S in literatures, the probabilistic matrix factorization model (PMF) is popular and useful to predict the missing rating values. PMF characterizes the observed rating data by assuming, the matrix factorization-based collaborative filtering

model. Intuitively, social network we focus on the social recommendation systems by integrating the social information into the matrix factorization-based collaborative filtering model.

1.2 Machine Learning

The study of computer algorithms that can automatically improve through experience and the use of data are known as machine learning (ML). It is thought to be a component of artificial intelligence. In order to make predictions or decisions without being explicitly programmed to do so, machine learning algorithms construct a model from sample data, or training data. When it is difficult or unfeasible to develop conventional algorithms that can carry out the required tasks, machine learning algorithms are utilized in a wide range of applications, including computer vision, speech recognition, email filtering, and medicine. Other applications include computer vision. Computational statistics, which focuses on making predictions with computers, is closely related to a subset of machine learning; but statistical learning is only one type of machine learning.

1.3 Matrix Factorization

An artificial neural network known as a feed forward neural network does not have cyclical connections between its nodes. As a result, it is distinct from its ancestor: networks of recurrent neurons the first and simplest artificial neural network was the feed forward neural network. The information in this network only moves forward from the input nodes, past any hidden nodes, and on to the output nodes. The network does not contain any cycles or loops. A single-layer perceptron network, which only has one layer of output nodes, is the simplest type of neural network. Through a series of weights, the inputs are fed directly to the outputs. In each node, the sum of the products of the weights and the inputs is calculated, and the neuron fires and takes the activated value (typically one) if the value is higher than a threshold, usually 0; Otherwise, it uses the value that has been disabled.

1.4 Social Recommendation

Intuitively, there is some interactions user behaviour because both of them have ability to describe the users' characteristics and provide useful information to identify the user communities. According to the social rationale social relationships may affect the user's decision-making behaviour. Meanwhile, user's behaviour may be an important influence on establishing his or her social relationships. For example, on the one hand, when Bob plans to see the movie —Interstellar, he will check whether his friend Alice did or not. On the other hand, Bob and Alice may join in a same hobby group because they both like the science fiction movie. Thus, unified social recommendation model is proposed in this paper. It aims to sufficiently mine the indirect relationship.

2. LITERATURE SURVEY

J.Kim et al, [2] has suggested. The high quality recommendation is important for online system to assist users who face a vast number of choices making effective selection decisions. Collaborative filtering is a widely accepted technique to provide recommendation based on rating of similar user. It is rating users trusted and merged to generating recommendation. Y.Rendle et al [3] has suggested. The current generation of recommended methods are usually classify into many categories content based, collaborative based, hybrid based various of current recommendation methods that can improve recommendation make recommender system applicable to an even broader range of the applications. A.Farahat et al, [4] has suggested. Data scalability and prediction quality have been recognize the challenges that every collaborative filtering algorithm or recommender system can neither handle very large data sets, then deal with the users who have made very few rating or even none at all. then the incorporate other contextual information. D.Liet al, [6] has suggested. Towards the next generation of Recommender System: A survey of the State-of-the-Art and possible Extensions. The Paper presents an overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into many categories that can improve recommendation capabilities and make recommender system applicable to an even broader range of applications. A.Mukherjee et al., [12] has suggested. A matrix factorization technique with trust propagation for recommendation in social networks Recommender Systems are becoming tools of choice to select the online information relevant to a given user. With the advent of online social networks the social network based approach recommendation has emerged.

3. EXISTING SYSTEM

Due to leveraging social relationships between as well as their past social behavior, social recommendation becomes a core component in recommendation systems. Most existing methods only consider direct social relationships among users (e.g. explicit and observed social relations). In this project, main contribution is to propose a new joint recommendation model taking advantage of the Indirect Social relations detection and Matrix Factorization collaborative filtering on social network and rating behavior information, which is called as In SRMF and rating behavior information, which is called as In SRME. In our work, the user latent factors can simultaneously

and seamlessly capture user's personal preferences and optimize the In SRMF model, we develop a parallel graph vertex programming algorithm for efficiently handling large scale social recommendation data. Indirect Social Relations detecting and the Matrix Factorization collaborative filtering on both social network and rating information, called as In SRMF. Furthermore, the proposed model has ability to handle the noise, the differences between users, and the differences between items by introducing the user and item biases, assuming different users follow different distributions according to the corresponding rating information, and similar to different items. Factors are iteratively identified. More specifically, the new model complexity and enables update procedure to finish in. The indirect social relation only by considering the user social information but ignoring the user behaviour information (e.g., rating data). The other is that they do not explicitly capture the natural relationship between indirect social relations and latent user/item factors. Intuitively, there are some interactions between social network and user behaviour because both of them have ability to describe the users' characteristics and provide useful information to identify the user communities. According to the social rationale social relationships may affect the user's decision-making behaviour. Meanwhile, the user's behaviour may be an important influence of social recommendation.

4. PROPOSED SYSTEM

In this project, we propose Trust SVD, a trust-based matrix factorization technique for recommendations. Trust SVD integrates multiple information sources into the recommendation model. 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. Trust SVD 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. Our proposed work focus on all recommendation tasks in recommender systems, namely item recommendation, rating prediction and Trust Estimation. Improved accuracy: Trust SVD has been shown to perform traditional matrix factorization approaches in terms of recommendation accuracy, especially in scenarios where there is sparse or noisy feedback data. Better handling of cold-start problem: Trust SVD can handle the cold-start problem better than traditional matrix factorization methods, by utilizing trust relationships between users even when there is little or no feedback data available for a new user. Robustness to noise and biases Trust SVD can effectively filter out noisy.

4.1 Input Dataset

All instances of missing variables in the form of nulls or noise were replaced by the OULAD's mean values to improve the predictive models' performance. For instance, the assessments table lacked the date values, which indicate when the assessments were taken and submitted. All date instances with N/A, null, or missing values were replaced by the date mean value because the date is an important variable in the early prediction of at-risk students.

4.2 Preprocessing

In machine learning and data mining, data preprocessing is used to make input data easier to work with in the preprocessing technique training set, which is a subset used to train a model. Test set—to divide the prediction of the trained method, a subset is used to test the trained model. Is sufficiently huge to yield genuinely significant outcomes. Is a good representation of the entire dataset.

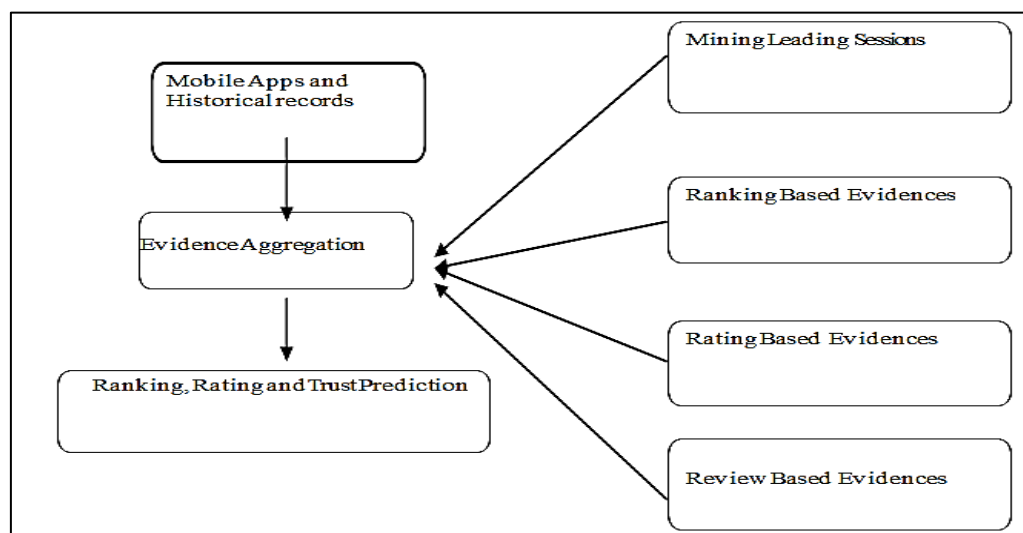


Figure 1. System Flow Diagram

To put it another way, you shouldn't select a test set that differs from the training set. Your objective is to develop a model that effectively adapts to new data, assuming that your test set satisfies the previous two conditions. New data can be compared to our test set.

5. ALGORITHMS

Classification is a term used in K-nearest neighbor (KNN) is a machine learning to describe a predictive. 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. The **In SRMF** aims to learn the latent user and item factors to complete the incomplete rating matrix with the aid of social information. In order to do this, it integrates social network and rating matrix together and represents the user/item in a consistent and compact feature space. Compared with Bayesian probabilistic generative models which should be optimized by approximate inference algorithm, such as variational inference, the proposed model **In SRMF** can be directly approximated by maximizing the posterior with the aid of gradient-based optimization technique. To be specific, in order to conveniently calculate the maximum.

Step 1: User should register it.

Step 2: If they are valid user they can login.

Step 3: Then user can view the apps.

Step 4: After user can rating the app

Step 5: User can ranking the app for the choice.

6. RECOMMENDATION PERFORMANCE

A series of experiments are conducted to compare the proposed **In SRMF** with thirteen base lines. Four different views are adopted to evaluate the recommendation performance of the proposed method and the existing methods. Among them, all users' views indicate that all ratings are used as the training set. Near cold start users view means that the users who rate less than five items will be involved in the training set, and pure cold start user's view indicates that users without any historical information in the training set. Long tail items view only considers the items which are in long tail. Obviously, most of the social recommendation methods significantly outperform rating only recommendation approaches (PMF and SVD++), which indicates considering social relations among users is beneficial for improving recommendation quality. In SRMF performs better than the existing social recommendation methods, which confirms that considering both observed and unknown social relations are helpful to extract social structure and leverage the recommendation model training. In SRMF has the ability to handle cold start problem and is superior to baselines in both cases. This result confirms that combining the indirect social relations identification and latent factors determination into a unified model is much more beneficial to social recommendation than two stage process.

Algorithm	Recommendation	Ranking	Rating	Accuracy
SVM	80	80	80	81
KNN	75	76	68	76
RF	99	98	99	99

Therefore, based on these observations we can say that **In SRMF** consistently outperforms the state of the art recommendation methods and significantly improves the recommendation performance.

7. EXPERIMENTAL RESULTS

In this section, we can demonstrate the performance of the proposed model from four facts. Firstly, we check the effect of the parameters on **In SRMF**. Secondly, it is compared to the existing eleven social recommendation methods from four views. Thirdly, we investigate how the social relations affect the corresponding social recommendation methods. Finally, the computational complexity and scalability analysis on real world datasets are given to show the efficiency of **In SRMF**.

8. CONCLUSION

In this paper, we focus on the community based recommendation which is rarely studied but attracts attention recently. To leverage the recommendation performance, we proposed a joint model **In SRMF** to effectively combine the social overlapping community detection and matrix factorization collaborative filtering. Meanwhile, an efficient parallel graph computing algorithm is designed to solve the model. The experiments on benchmark datasets showed that **In SRMF** is consistently superior to the state of the art approaches in the settings, including recommendation on All Users, near cold start users, pure cold start users, Long tail items and users with different social degrees. Moreover, tracking the temporal

dynamics of user preference to items is a challenge, and temporal information has been proved very useful in improving quality of predictions. Thus, we tend to further improve the proposed model by considering dynamical temporal information of social relations and ratings information. Meanwhile, we could integrate other available multiple resources such as item content, user-user interaction information.

9. REFERENCES

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