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A Trust-based recommendation system with item rating and user hope information

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ABSTRACT:

A trust-based matrix factorization technique for recommendations is Web Based Machine Learning 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. In this article, we propose a novel trust-based recommendation model regularized with user trust and item ratings, termed as Web based machine learning. Our approach builds on top of a state of- the-art model through which both the explicit and implicit influence of user-item ratings are involved to generate predictions.

KEYWORDS: Recommender systems, collaborative filtering, Trust SVD.

1. INTRODUCTION

Recommender systems have been widely used to provide users high-quality personalized recommendations for the users from a large amount of choices .Robustness and accuracy rate recommendations are the importance of e-commerce operations like navigating product offerings, personalization, improving customer satisfaction, and in marketing like tailored advertising, segmentation, cross-selling. A novel trust-based recommendation model regularized with user trust and item ratings, termed as Web based machine learning is used in this paper. Our approach builds on top of a state of- the-art model through which both the explicit and implicit influence of user-item ratings are involved to generate predictions.

1.1 PROBLEM STATEMENT

Collaborative filtering (CF) is one of the most popular techniques to implement a recommender system. However, CF suffers from two well known issues: data sparsity and cold start [1]. The former issue refers to the fact that users usually rate only a small portion of items while the latter indicates that new user 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. In order to avoid this novel trust-based recommendation model regularized with user trust and item ratings, termed as Web based machine learning is used in this paper. Our approach builds on top of a state of- the-art model through which both the explicit and implicit influence of user-item ratings are involved to generate predictions.

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2. LITERATURE SURVEY

2.1RELATED WORK

Although demonstrated to be efficient and scalable to large-scale data sets, clustering-based recommender systems suffer from relatively low accuracy and coverage. To address these issues, we develop a multi-view clustering method through which users are iteratively clustered from the views of both rating patterns and social trust relationships.

To accommodate users who appear in two different clusters simultaneously, we employ a support vector regression model to determine a prediction for a given item, based on user-item- and prediction-related features. So this is approach expose low accuracy and low coverage of data. Trust has been used to replace or complement rating based similarity in recommender systems, to improve the accuracy of rating prediction. However, people may not always share similar preferences.

In this paper, we try to fill in this gap by decomposing the original single-aspect trust information into four general trust aspects, i.e. benevolence, integrity, competence, and predictability, and further employing the support vector regression technique to incorporate them into the probabilistic matrix factorization model for rating prediction in recommender systems. Experimental results on four datasets demonstrate the superiority of our method over the state-of-the-art approaches. Collaborative filtering suffers from the problems of data sparsity and cold start, these problems degrade recommendation performance. To help resolve these issues, many researchers [2], [3],[4], [5], [6] attempt to incorporate social trust information into their recommendation models, given that model-based CF approaches outperform memory-based ones. To help resolve these issues, we propose Trust SVD, a trust-based matrix factorization technique. By analyzing the social trust data from four real-world data sets, we conclude that not only the explicit but also the implicit influence of both ratings and trust should be taken into consideration in a recommendation model. Yuan etal. [8]

Find that trust networks are small-world networks where two random users are socially connected in a small distance, indicating the implication of trust in recommender systems. In fact, it has been demonstrated that incorporating the social trust information of users is able to improve the performance of recommendations. There are two types of recommendation tasks in recommender systems, they are item recommendation and rating prediction. Most algorithmic approaches are only (or best) designed for either one of the recommendations tasks, and our work focus on the rating prediction task[10].

3. ANALYSIS OF FRAMEWORK

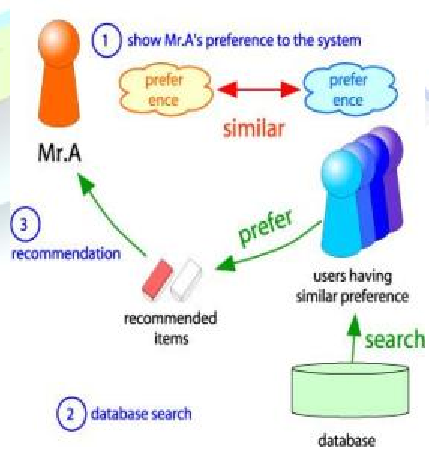

FIG 1.System Architecture

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1. Dynamic Recommendation Module:

Personalized recommendation is a desirable way to improve customer satisfaction and retention. There are mainly three approaches to recommendation engines based on different data analysis methods, i.e., rule-based, content-based and collaborative filtering. Among them, collaborative filtering (CF) requires only data about past user behavior like ratings, and its two main approaches are the neighborhood methods and latent factor models. The neighborhood methods can be user-oriented or item-oriented. They try to find like-minded users or similar items on the basis of co-ratings, and predict based on ratings of the nearest neighbors. Latent factor models try to learn latent factors from the pattern of ratings using techniques like matrix factorization and use the factors to compute the usefulness of items to users.

2. Relation Mining Of Rating Data Module:

For the sparsity of recommendation data, the main difficulty of capturing users' dynamic preferences is the lack of useful information, which may come from three sources-user profiles, item profiles and historical rating records. Traditional algorithms heavily rely on the co-rate relation (to the same item by different users or to different items by the same user), which is rare when the data is sparse. Useful ratings are discovered using the co-rate relation, which is simple, intuitional and physically significant when we go one or two steps along, but it strongly limits the amount of data used in each prediction.

3. Dynamic Feature Extraction Module:

Users' preferences or items' reputations are drifting, thus we have to deal with the dynamic nature of data to enhance the precision of recommendation algorithms, and recent ratings and remote ratings should have different weights in the prediction. These methods help to make progress in precision of dynamic recommendation, but they also have their weaknesses: decay functions cannot precisely describe the evolution of user preferences and only isolating transient noise cannot catch up with the change in data.

4. Multiple Phase of Interest Module:

A set of dynamic features to describe users' multi-phase preferences in consideration of computation, flexibility and accuracy. It is impossible to learn weights of all ratings for each user, but it is possible to learn the general weights of ratings in the user's different phases of interest if the phases include ranges of time that are long enough.

5. Collaborative filtering:

In this module Collaborative Filtering, or pattern recognition is used for large datasets of multiple users. These datasets can contain preferences of users for certain items. For example, YouTube members can rate a video by assigning a number of stars. The number of stars is a user's preference value, a value from 1 to 5. Based on this collection of personal preferences and a 'similarity function' you can recommend videos to users or determine similar users, users with similar taste in videos. In this case, recommending videos is an example of an 'item-based recommendation' and determining users with similar tastes is an example of an 'user-based recommendation'. [7] discussed about a method, In vehicular ad hoc networks (VANETs), because of the nonexistence of end-to-end connections, it is essential that nodes take advantage of connection opportunities to forward messages to make end-to-end messaging possible. Thus, it is crucial to make sure that nodes have incentives to forward messages for others, despite the fact that the routing protocols in VANETs are different from traditional end-to-end routing protocols. In this

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paper, stimulation of message forwarding in VANETs is concerned.

3.1ALGORITHM

3.1.1.K-meansClusteringAlgorithm:

***K-means* clustering** is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. *K-means* clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. The problem is computationally difficult (NP-hard); however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centers to model the data; however, *k*-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.

3.1.2Adaptive weighting algorithm:

These algorithms maintain the cumulative second-moment of the input features, and its inverse, qualitatively speaking, is used as a learning rate. Thus, if there is a single feature with large second-moment in the prefix of the input sequence, its effective learning rate would drop to a relatively low value, and the learning algorithm will take more time to update its value. When the instances are ordered such that the value of this feature seems to be correlated with the target label, such algorithms will set the value of weight corresponding to this feature to a wrong value and will decrease its associated learning rate to a low value. This combination makes it hard to recover from the wrong value set to the

weight associated with this feature. Our final contribution is a new algorithm that adapts the way the second order information is used.

As features like *feas,d* (s = 1, 2, ..., d = 1, 2, ...) gained by applying *Multiple Phase Division* are all normalized rating values, in other words, as content of user and item profiles have been quantified in the feature extraction, it is convenient for us to organize them for accurate rating estimation by adaptive weighting. Sizes of the relevant subsets are also recorded in MPD and could reflect data density. We incorporate these features for recommendation with a linear model since they are homogeneous and it is efficient to learn their weights.

4. CONCLUSION

This article proposed a novel trust-based matrix factorization model which includes both. Analysis of trust in four real-world data sets indicated that trust and ratings were complementary to each other, and both important for more accurate recommendations. Our novel approach, Trust SVD, includes 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 to further regularize the generation of user- and item-specific latent.

5. REFERENCES

1. G. Guo, J. Zhang, and D. Thalmann, “A simple but effective method to incorporate trusted neighbors in recommender systems,”in

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Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
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Proceedings of the 20th International Conference on User Modeling, Adaptation and Personalization (UMAP), 2012, pp. 114–125.

2. H. Ma, H. Yang, M. Lyu, and I. King,

"SoRec: social recommendation using probabilistic matrix factorization," in

Proceedings of the 31st International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2008, pp. 931–940.

3. H. Ma, D. Zhou, C. Liu, M. Lyu, and I. King, "Recommender systems with social regularization," in Proceedings of the 4th ACM

International Conference on Web Search and Data Mining (WSDM),2011, pp. 287–296.

4. M. Jamali and M. Ester, "A matrix factorization technique with trust propagation for recommendation in social networks," in Proceedings of the 4th ACM Conference on Recommender Systems(RecSys), 2010, pp. 135–

142.

5. B. Yang, Y. Lei, D. Liu, and J. Liu, "Social collaborative filtering by trust," in Proceedings of the 23rd International Joint Conference on

Artificial Intelligence (IJCAI), 2013, pp. 2747– 2753.

6. H. Fang, Y. Bao, and J. Zhang, "Leveraging decomposed trust in probabilistic matrix factorization for effective recommendation," in Proceedings of the 28th AAAI Conference on Artificial Intelligence

(AAAI), 2014, pp. 30–36.

7. Christo Ananth, Kavya.S., Karthika.K., Lakshmi Priya.G., Mary Varsha Peter, Priya.M., "CGT Method of Message forwarding", International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE), Volume 1, Issue 1, August 2015,pp:10-15

8. W. Yuan, D. Guan, Y. Lee, S. Lee, and S.

Hur, "Improved trustaware recommender system using small-worldness of trust networks,"Knowledge-Based Systems, vol. 23, no. 3, pp. 232–238, 2010.

9. Guibing Guo, Jie Zhang, and Neil Yorke-Smith" A Novel Recommendation Model Regularized

with User Trust and Item Ratings" IEEE Transactions on Knowledge and Data Engineering.

10. W. Yuan, D. Guan, Y. Lee, S. Lee, and S.

Hur, "Improved trustaware recommender system using small-worldness of trust networks,"Knowledge-Based Systems, vol. 23, no. 3, pp. 232–238, 2010.