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Social Recommendation System for Real World Online Applications

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Abstract: Social recommendation system has attracted a lot of attention recently in the research communities of information retrieval, machine learning and data mining. Traditional social recommendation algorithms are often based on batch machine learning methods which suffer from several critical limitations, e.g., extremely expensive model retraining cost whenever new user ratings arrive, unable to capture the change of user preferences over time. Therefore, it is important to make social recommendation system suitable for real world online applications where data often arrives sequentially and user preferences may change dynamically and rapidly. In this paper ,present a new framework of online social recommendation from the viewpoint of online graph regularized user preference learning(OGRPL), which incorporates both collaborative user-item relationship as well as item content features into an unified preference Learning process. I further develop an efficient iterative procedure, OGRPL-FW which utilizes the Frank-Wolfe algorithm, to solve the proposed online optimization problem.

Keywords: Online Social recommendation, low rank, OGRPL, user preference learning

I. INTRODUCTION

Most traditional social recommendation algorithms are based on batch training techniques which assume all user ratings are provided in the user-item matrix. Such assumption makes them unsuitable for real-world online recommendation applications. First, the user ratings arrive sequentially in online applications. The batch recommendation algorithm has to be retrained from scratch whenever new ratings are received, making the training process extremely time-consuming. Moreover, if the size of training data is too large, it is difficult for handling all the data in the batch mode. Second, it is common that user preference could drift over time in real-world online application, which make the batch learning processes fail to capture such changes on time. To overcome these difficulties, we develop a novel frame work of social recommender system termed Online Graph Regularized User Preference Learning (OGRPL). In the task of online recommendation, the number of user ratings collected at each timestamp is much smaller than the ratings in the offline recommendation, which means all the items have to be recommended in a cold-start manner.

Currently, social networking and knowledge sharing sites like Twitter and Douban are popular platforms for users to generate shared opinions for the items like item review and summary [14]. Thus, the user generated content provides the auxiliary information for the items, which has been widely used to tackle the problem of cold-start item [9]. Unlike the existing online collaborative filtering methods,

OGRPL is a hybrid model utilizing both CF information via the partially observed user item matrix as well as the auxiliary content features for each item. Given a stream of user ratings, OGRPL incrementally learns the user preference on the content features of the items. However, humans are are prone to make rating errors and the rating data always contain noise in practice. Thus, the direct learning of user preference may be over-fitting and is the refore not robust. To overcome the over fitting problem, we formulate the problem of user preference learning with low rank constraints and learn the low-rank representation of user preference. A common practice to solve the learning problem with low-rank constraints is to relax the rank constraint to a convex trace norm constraint, which uses the full singular value decomposition operator in the projected gradient descent optimization method. However, the cubic time complexity of computing full singular value decomposition is extremely time-consuming for online learning. Then develop an efficient iterative procedure to solve the online optimization problem with only computing the top singular value. The OGRPL model recommends the items based on user preference in the online manner. When the recommended items come, users give the rating to the items. We denote that the users who give the high ratings by red circle, the ones who give the low ratings by green circle and others who don't give the ratings by grey circle in Figure The users' ratings are sequentially collected and stored in the system. Then, the OGRPL model updates the user preference based on the newly observed users' ratings and their social relations.

II. METHODOLOGY OF PROPOSED SYSTEM

A. Problem Statement

Formulate the problem of user preference learning with low rank constraints and learn the low-rank representation of user preference. A common practice to solve the learning problem with low-rank constraints is to relax the rank constraint to a convex trace norm constraint, which uses the full singular value decomposition operator in the projected gradient descent optimization method However, the cubic time complexity of computing full singular value decomposition is extremely time-consuming for online learning. We then develop an efficient iterative procedure to solve the online optimization problem with only computing the top singular value.

III. SYSTEM ARCHITECTURE

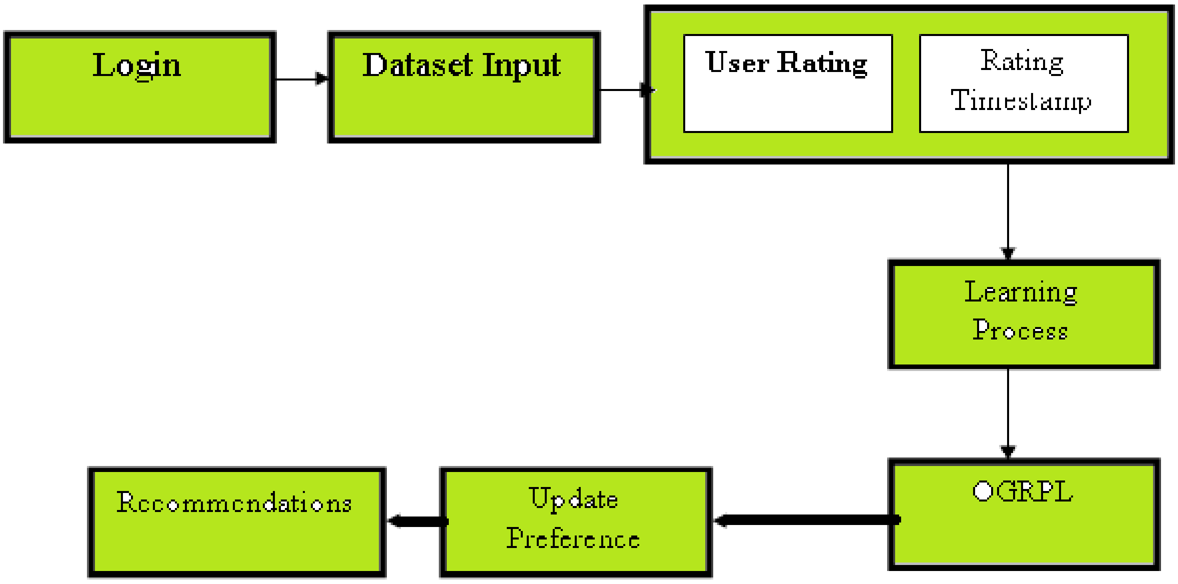

Fig. 1 System Architecture

Present a new framework of online social recommendation from the viewpoint of graph regularized user preference learning, which incorporates both collaborative user-item relationship as well as item content features into an unified preference learning process.

Develop an efficient iterative procedure, OGRPL-FW which utilizes the Frank-Wolfe algorithm, to solve the proposed online optimization problem.

Conduct extensive experiments on several large-scale datasets, in which the encouraging results demonstrate that the proposed algorithms obtain significantly lower errors (in terms of both RMSE and MAE) than the state-of-the-art online recommendation methods when receiving the same amount of training data in the online learning process.

The main procedure of the ADMM algorithm to this problem can be described as follows:

1) Introduce the auxiliary variable for user preference matrix **W**, and devise the augmented Lagrange function that decomposes the original problem into the problem of user preference learning and the problem of rank minimization with respect to the lag range terms.

2) The problem of user preference learning can be solved with closed form solution.

3) The problem of rank minimization with respect to the flag range terms can be solved using full singular value decomposition.

B. Algorithms

- Frank-Wolfe algorithm,
- The Optimization using OGRPL-FW
- ADMM algorithm

III. PROPOSED SYSTEM

Several aspects of the proposed approach here:

- Present a new framework of online social recommendation from the viewpoint of graph regularized user preference learning, which incorporates both collaborative user-item relationship as well as item content features into a unified preference learning process.

- Develop an efficient iterative procedure, OGRPL-FW which utilizes the Frank-Wolfe algorithm, to solve the proposed online optimization problem.

- Conduct extensive experiments on several large-scale data sets, in which the encouraging results demonstrate that the proposed algorithms obtain significantly lower errors (in terms of both RMSE and MAE) than the state-of-the-art online recommendation methods when receiving the same amount of training data in the online learning process.

A. Objectives & Scope of Proposed System

- To capture the change of user preferences over time.

- Social recommendation system suitable for real world online applications.

- To develop and incorporates both collaborative user-item relationship as well as item content features into an unified preference learning process.

- To explore the non-linear user preference learning function as the user model for the problem of online social recommendation.

B. Advantages

- Less retraining cost whenever new user ratings arrive.

- Suitable for real world online applications.

C. Application Areas

- Online Social Websites

- Advertisement System

- Ecommerce Application

CONCLUSION

In this paper, presented a new framework of online social recommendation from the viewpoint of online user preference learning, which incorporates both collaborative user-item relationship as well as item content features into a unified preference learning process. I consider that the user model is the preference function which can be online learned from the user-item rating matrix. Furthermore, our approach integrates both online user preference learning and users' social relations seamlessly into a common framework for the problem of online social recommendation. In this way, our method can further improve the quality of online rating prediction for the missing values in the user-item rating matrix. I devise an efficient iterative procedure, OGRPL-FW to solve the online optimization problem. We conduct extensive experiments on several large-scale datasets, in which the encouraging results demonstrate that our proposed algorithm achieves better performance than the state-of-the-art online recommendation methods.

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