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Social Recommendation System for Real World Online Application

Pranali M. Sonawane
Department of Computer Engineering
SVIT,Chincholi

Prof. S. M. Rokade
Department of Computer Engineering
SVIT,Chincholi

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, we 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 a 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, User Preference Learning, Low Rank

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 assumptions make them unsuitable for real-world online recommendation applications. First, the user ratings arrive sequentially in an 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 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 reform 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.

Illustrate the online graph regularized user preference learning in online social recommender system in Figure 1.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. REVIEW OF LITERATURE

Sanjay Purushotham, Yan Liu, C.-C. Jay Kuo "Collaborative Topic Regression with Social Matrix Factorization for Recommendation Systems" : International Conference on Machine Learning, dinburgh, Scotland, UK, 2012.Propose a hierarchical

Bayesian model to integrate social network structure (using matrix factorization) and item content-information (using LDA model) for item recommendation. Connect these two data sources through the shared user latent feature space. The matrix factorization of social network will learn the low-rank user latent feature space, while topic modelling provides a content representation of the items in the item latent feature space, in order to make social recommendations.

Emmanuel J. Cand`es and Yaniv" Matrix Completion with Noise" N00014-09-1-0469 and N00014-08-1-0749 2009, this paper reviewed and developed some new results about matrix completion. By and large, low-rank matrix recovery is a field in complete infancy abounding with interesting and open questions, and if the recent avalanche of results in compressed sensing is any indication, it is likely that this field will experience tremendous growth in the next few years.

Tom Chao Zhou, Hao Ma, Michael R. Lyu and Irwin King" User Rec: A User Recommendation Framework in Social Tagging Systems" AAAI Conference 2010, Propose an effective framework for users' interest modelling and interest-based user recommendation in social tagging systems, which can help information sharing among users with similar interests. Specifically, we analyse the network and fans properties, and we observe an interesting finding that the role of users have similar properties with Web pages on the Internet.

III. SYSTEM ARCHITECTURE

Online graph regularized user preference learning in online social recommender system in fig

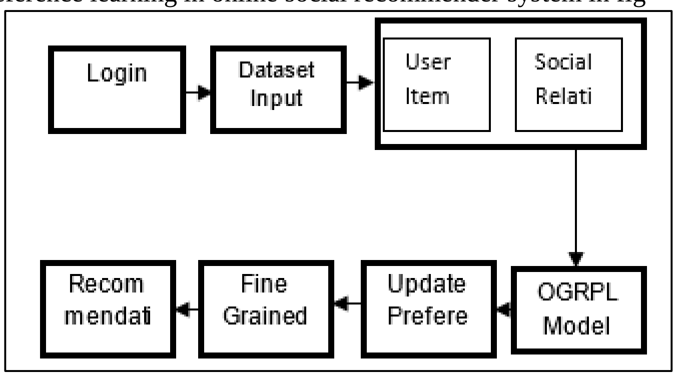


Fig. 1: System Architecture

When the recommended items come in data, user will give rating to items like high or low according to their social relation. Then OGRPL model will update the preference based on newly observed user social relation and user rating .with help of fine grained model we finally obtain system recommendation.

A. Frank –Wolfe Algorithm

Frank –Wolfe algorithm is also called as gradient method. This algorithm solve optimization problem

Initialization: Let $k \leftarrow 0$, and let x_0 be any point in D.

Step 1: Direction-finding sub problem: Find s_k solving

Minimize $s^T \Delta f(X_k)$

Subject to $s \epsilon D$

Step 2: Step size determination: Set $\Upsilon \leftarrow 2/k+2$, or alternatively find Υ that minimize $f(X_k + \Upsilon(S_k - X_k))$ Subject ti $0 \leq \Upsilon \leq 1$.

Step 3: Update: Let $X_{k+1} \leftarrow X_k + \Upsilon(S_k - X_k)$. Let $k \leftarrow k+1$ and go to Step 1.

B. Optimization using OGRPL-FW

The OGRPL-FW method can decomposed into two procedures direction finding procedure and online updating procedure

Input: Laplacian matrix L, item content matrix X, constant parameter $a \geq 0$ and a sequential collection of user ratings with indices $\Omega 1, \ldots \Omega k$

Output: User preference matrix W_K

1) Initialize user preference W_1 randomly, such that $\|W1\|_* \leq \Upsilon$
2) for T = 1; 2; ..;K do
3) Compute $V_T \leftarrow \arg \min_{\|W\|_* < \Upsilon} \{\nabla F(W_T) \cdot W\}$
4) Update $W_T+1 = (1 - {}_T{}^{-a})W_T + T^{-a} V_T$
5) return User preference matrix W_K

IV. SOFTWARE REQUIREMENT

A. Hardware Interfaces

Processor: Pentium 4.0 GHz or higher

RAM: 512 Mb or more
Hard Drive: 50 GB or more

B. Software Interface

IDE: Microsoft visual studio 2010
OS: Windows XP/2000/Vista
Language: C#.
Framework: .Net Framework 4.0

V. MATHEMATICAL MODEL & DESIGN

1) U= {IR, MT, CM, FM, OR}
IR=Set of Input ratings
MT= Model Training
CM = Set of content matrix
FM = Set of fine-grained model
OR = Set of Recommendation Output.
2) F1 = set of functions which will pre- process input data.
F2 = Set of functions that apply Optimization using OGRPL algorithm.
F3 = Set of functions that apply Frank-Wolfe algorithm.
F4 = Set of functions that generate results.
3) Basic Data structured used is array
4) System is based on oops concepts.
5) System is in NP complete state

VI. IMPLEMENTATION STATUS

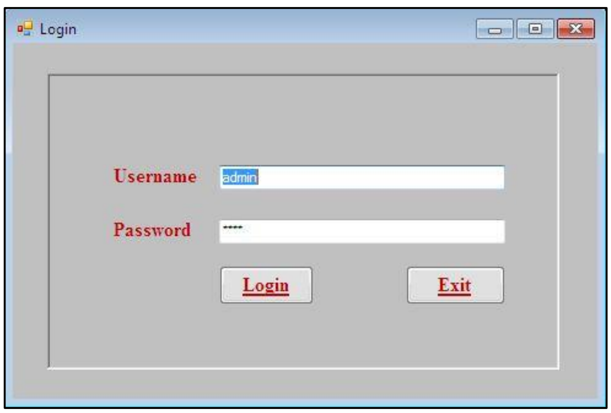


Fig. 2: Login Page

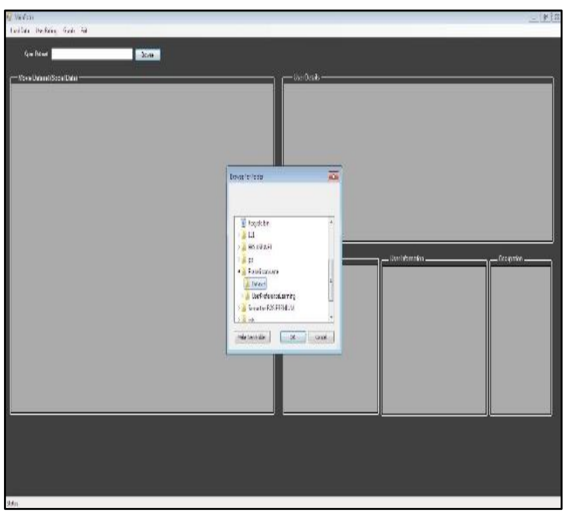


Fig. 3: Selection of Movie Dataset

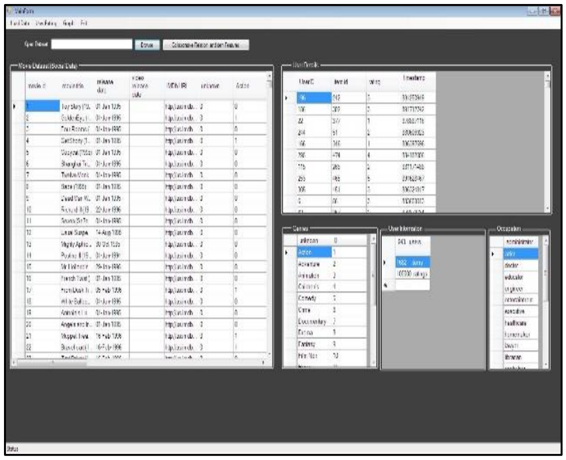


Fig. 4: Dataset

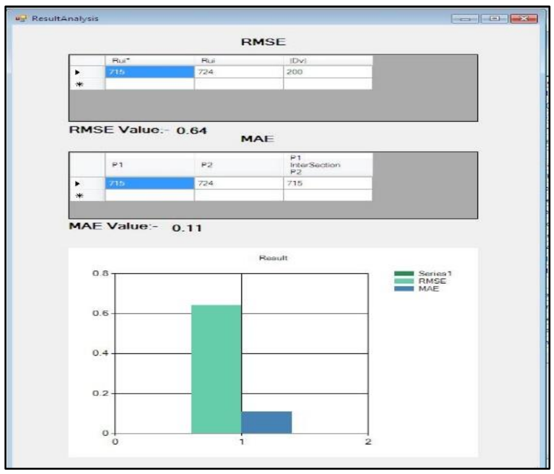
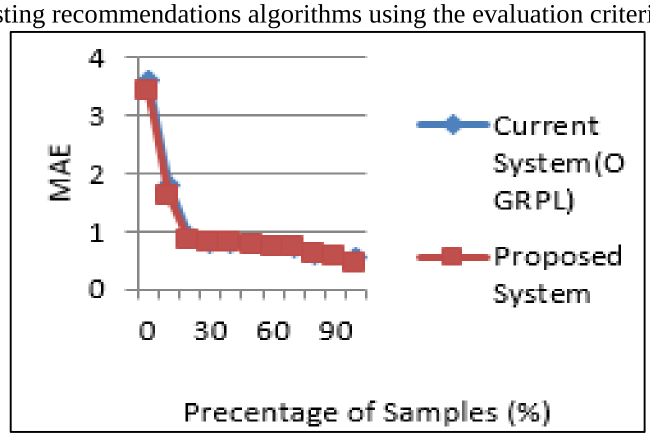


Fig. 5: Result Analysis

Firstly we had implement Item content feature in recommender systems using bag-of-words model.
Than item review by users in the recommender system as the content feature of the items.

VII. PERFORMANCE MEASURES USED

We compare our method with existing recommendations algorithms using the evaluation criteria MAE and RMSE.



Graph 1: Comparison Existing System

VIII. EFFICIENCY CALCULATION

We study the efficiency of our method using two datasets. The experimental results on MAE using Douban Movie data. On the other hand, we illustrate the online performance of our method using Douban Music data on MAE in Figures above.

IX. Outcome & success definition of work

We presented a new framework of online social recommendation from the viewpoint of online user preference learning, which incorporates both collaborative user-item relationships well as item content features into a unified preference learning

X. Conclusion

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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