

COLLABORATIVE FILTERING BASED ON OBJECTIVE TYPICALITY FOR NEIGHBOUR RECOMMENDATION

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Abstract:

Collaborative filtering (CF) is an important and popular technology for recommender systems. However, current CF methods suffer from such problems as data sparsity, recommendation inaccuracy, and big-error in predictions. In this paper, we borrow ideas of object typicality from cognitive psychology and propose a novel typicality-based collaborative filtering recommendation method named TyCo. A distinct feature of typicality-based CF is that it finds —neighbors of users based on user typicality degrees in user groups (instead of the corated items of users, or common users of items, as in traditional CF). To the best of our knowledge, there has been no prior work on investigating CF recommendation by combining object typicality. TyCo outperforms many CF recommendation methods on recommendation accuracy (in terms of MAE) with an improvement of at least 6.35 percent in Movielens data set, especially with sparse training data (9.89 percent improvement on MAE) and has lower time cost than other CF methods. Further, it can obtain more accurate predictions with less number of big-error predictions.

Index Terms—Recommendation, typicality, collaborative filtering

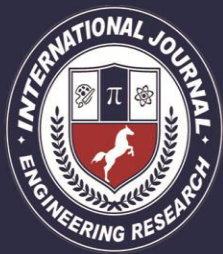
I. INTRODUCTION

Collaborative filtering (CF) is an important and popular technology for recommender systems. There has been a lot of work done both in industry and academia. These methods are classified into user-based CF and item-based CF. The basic idea of user-based CF approach is to find out a set of users who have similar favor patterns to a given user (i.e., “neighbors” of the user) and recommend to the user those items that other users in the same set like, while the item-based CF approach aims to provide a user with the recommendation on an item based on the other items with high correlations (i.e., “neighbors” of the item). In all collaborative filtering methods, it is a significant step to find users’ (or items’) neighbors, that is, a set of similar users (or items). For instance, Raymond is a very typical member of the concept “users who like war movies” while not so typical in the concept “users who like romance movies.” The typicality of users in different user groups can indicate the user’s favor or preference on different kinds of items. The typicality degree of a user in a particular

user group can reflect the user’s preference at a higher abstraction level than the rated items by the user.

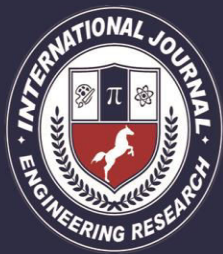
II. RELATED WORK

[1] Collaborative filtering (CF) is an important and popular technology for recommender systems. However, current CF methods suffer from such problems as data sparsity, recommendation inaccuracy and big-error in predictions. In this paper, we borrow ideas of object typicality from cognitive psychology and propose a novel typicality-based collaborative filtering recommendation method named TyCo[13]. A distinct feature of typicality-based CF is that it finds “neighbors” of users based on user typicality degrees in user groups (instead of the co-rated items of users, or common users of items, as in traditional CF). To the best of our knowledge, there has been no prior work on investigating CF recommendation by combining object typicality. TyCo outperforms many CF recommendation methods on recommendation accuracy (in terms of MAE) with an improvement of at least 6.35% in Movie lens Data set, especially



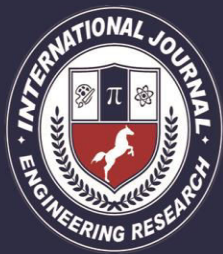
with sparse training data (9.89% improvement on MAE) and has lower time cost than other CF methods[11]. [2]To solve this problem, the recommendation system based on collaborative filtering is applied to the simulation resource management system, which can recommend the most relative simulation resource to the user according to user's previous preference. From this paper we referredAfter analyzing the necessity of combining the recommendation system with the Simulation resource system, the simulation resource recommendation system is designed and realized. The realization includes three main procedures: collecting user preferences, finding neighbor users, recommending simulation resources. The recommendation system collects users' grading on used simulation resources as user preferences, and uses the Pearson correlation to calculate the similarity between users and then finds out the neighbor users. Our proposed method, a collaborative filtering method to provide an enhanced recommendation quality derived from user-created tags. Collaborative tagging is employed as an approach in order to grasp and filter users' preferences for items. In

addition, we explore several advantages of collaborative tagging for data sparseness and a cold-start user. These applications are notable challenges in collaborative filtering[13]. [3]Empirical experiments using a real dataset from del.icio.us. Experimental results show that the proposed algorithm offers significant advantages both in terms of improving the recommendation quality for sparse data and in dealing with cold-start users as compared to existing work. Recommendation systems are widely used to recommend products to the end users that are most appropriate online book selling websites now-a-days are competing with each other by many means. Recommendation system is one of the stronger tools to increase profit and retaining buyer. The book recommendation system must recommend books that are of buyer's interest. This paper presents book recommendation system based on combined features of content filtering, collaborative filtering and association rule mining[4]. [4]The hybrid recommender system with temporal information is best method from all methods which we have studied. Because it constructs offline to make the



recommendation system to recommend item for a user within user bearable time which will also reduce the computational time. Also, it solves scalability, sparsity and cold start issue and provides final recommendation quickly and accurately. Recommender systems provide an important response to the information overload problem as it presents users more practical and personalized information services. Collaborative Filtering technique is the most successful in the recommender systems field. Collaborative filtering creates suggestions for users based on their neighbor's preferences. But it suffers from poor accuracy, scalability and cold start problems[12]. [5]The tremendous growth of the number of customers and products in recent years poses some key challenges for recommender systems in which high quality recommendations are required and more recommendations per second for millions of customers and products need to be performed. Thus, the enhancement of scalability and efficiency of collaborative filtering (CF) algorithms become progressively more important and difficult.[9] This paper focuses on study of

different collaborative filtering algorithms taking into consideration the scalability issue. The different algorithms studied are cluster based, item based and context based. There are many recommendation system for tour packages, but they fail to create a package that suite the customer need. The unique characteristics of travel data are area of interest, session and travel mode. The tour spots are distributed in many geographical locations. [6]The topic extraction is conditioned on both the tourists and the intrinsic features like locations travel seasons, mode of transport. The TRAST model scans the locations where most of the users like. Then the locations are filtered by session (eg: winter, summer). Then the filtered set is again filtered by travel mode like bus, car, van etc... Finally a tour package is created which is the best suited to the customer needs. According to the topic model representation, a cocktail approach is generated so that to form lists for personalized travel package recommendation. The TAST model is extended to the touristrelation-area-season topic (TRAST) model for collecting the relationships among the tourists for all travel



groups. Then analyze TAST model, TRAST model, and cocktail recommendation approach on the current travel package data. The TAST model can effectively grab the individual characteristics of travel data and cocktail approach, so it is more efficient than old recommendation techniques for travel package recommendation by including tourist relationships, TRAST model is used as an effective evaluation for travel group formation[8].

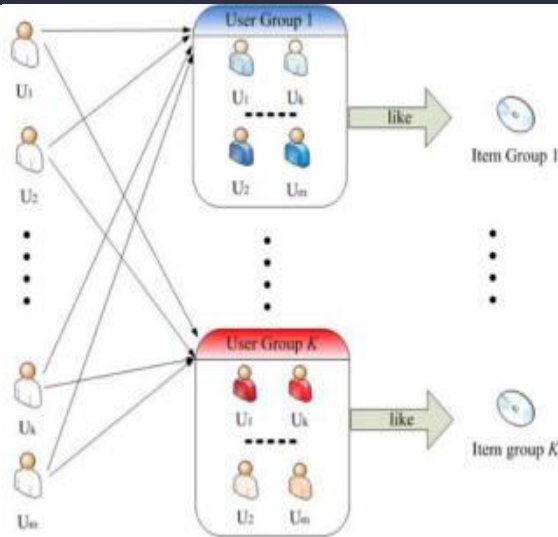
III. TYPICALITY-BASED

COLLABORATIVE FILTERING

In this section, we propose a typicality-based collaborative filtering approach named TyCo, in which the “neighbors” of users are found based on user typicality in user groups instead of co-rated items of users. We first introduce some formal definitions of concepts in TyCo in Section 3.1. The mechanism of TyCo is then described in Section 3.2. We introduce its technical details in Sections 3.3, 3.4, 3.5, and 3.6. 3.1 Preliminaries Assume that in a CF recommender system, there are a set U

of users, and a set O of items. Items can be clustered into several item groups and an item group is intuitively a set of similar items. For example, movies can be clustered into action movies, war movies, and so on. Each movie belongs to different movie groups to different degrees. The choice of clustering method is application domain dependent, and is out of the scope of this paper. For instance, based on the keyword descriptions of movies, we can use Topic Model-based clustering [30], [31] for the task of obtaining movie groups and the degrees of movies belonging to movie groups. In other application domains, other clustering approaches (such as [32], [33]) can also be used. In this paper, we will not discuss clustering methods further.

The formal definition of an item group is given in the following



The relations among users, user groups, and item groups are as shown in Fig. 1. Users possess different typical degrees in different user groups: the darker a user is in Fig. 1, the more typical it is in that user groups. For examples, U_1 and U_k are typical in user group g_k but not typical in g_1 , while U_2 and U_m are typical in g_1 but not typical in g_k . For the reason that users have different typicality degrees in different user groups, we represent a user by a user typicality vector defined below

3.2 Mechanism of TyCo The mechanism of TyCo is as follows: given a set $O = \{o_1, o_2, \dots, o_h\}$ of items and a set $U = \{u_1, u_2, \dots, u_m\}$ of users, a set $K = \{k_1, k_2, \dots, k_n\}$ of item groups is formed. For each item group k_i , there is a corresponding user

group g_i . Users have different typicality degrees in each g_i . Then, a user typicality vector U_i is built for each user, from which user-typicality matrix M_{TyCo} is obtained. After obtaining users similarity based on their typicality degrees in user groups, a set N_i of “neighbors” is obtained for each user. Then, we predict the rating of an active user on an item based on the ratings by “neighbors” of that user on the same item.

	g^1	g^2	g^3	g^4	g^5	g^6
U_1	0.87	0.75	0.92	0.12	0.32	0.28
U_2	0.34	0.21	0.38	0.89	0.85	0.94
\vdots
U_k	0.81	0.79	0.89	0.15	0.29	0.31
\vdots
U_m	0.41	0.22	0.35	0.90	0.88	0.92

Fig. 2. An example of user-typicality matrix in TyCo.

3.3 Neighbors Selection

We select a fuzzy set of “neighbors” of user U_j , denoted by N_j , by choosing users who are sufficiently similar to U_j , i.e., $N_j = \{U_i \mid \text{Sim}(U_i, U_j) \geq \theta\}$; where $\text{Sim}(U_i, U_j)$ is the similarity of U_i and U_j and θ is a threshold to select users who are qualified as “neighbors” of user U_j . represented by a set

of properties, which, following our previous work [34], we shall call item property vector. For example, keywords, actors, directors, and producers are properties of a movie and these properties can form an item property vector to represent a movie. For each item group k_j , we can extract a prototype to represent the item group. The prototype of k_j is represented by a set of properties denoted by the prototype property vector of k_j t_{kj} , as follows: $t_{kj} = \{p_{kj;1}; p_{kj;2}; \dots; p_{kj;m}\}$, where m is the number of the properties of the prototype of concept (item group) k_j , and $r_{kj;i}$ is a real number (between 0 and 1), which indicates the degree the prototype of concept k_j possesses the property $p_{kj;i}$.

The typicality of an item O_y in an item group k_j , denoted by $w_{j;y}$, depends on the similarity between the item O_y and the prototype of k_j

	i_1	i_2	\dots	i_k	\dots	i_n
U_1	5	?	...	3	...	4
U_2	?	?	...	4	...	5
\vdots
U_k	2	5	...	?	...	3
\vdots
U_m	5	4	...	2	...	?

IV. EXPERIMENTAL SETUP

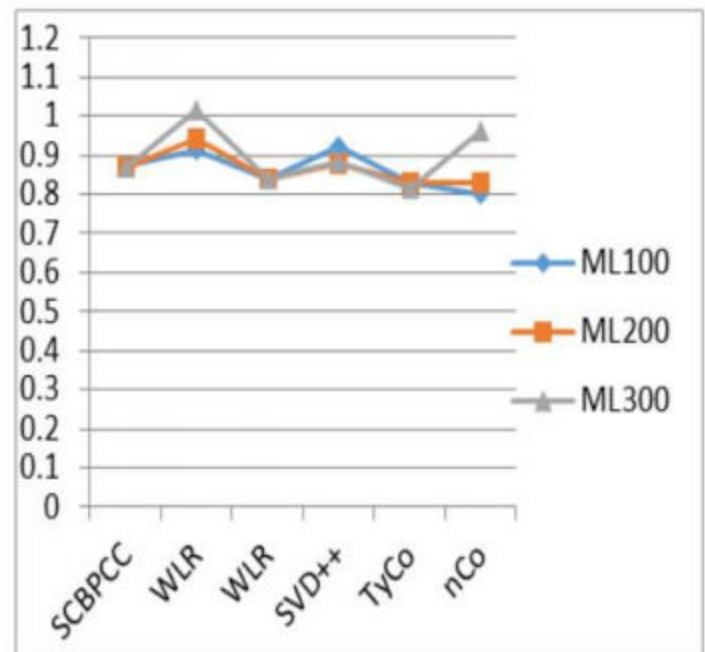
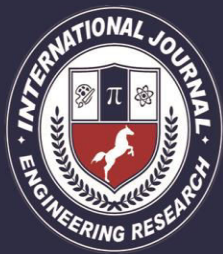


Fig. 04 Comparison of State-Of-The-Art Methods on MAE

From the projectwork someanalysis between different techniques has been made. The following table shows the comparison with



state-of-the art methods on MAE which includes SCBPCC, WLR, CBT, SVD++, TyCo[13]

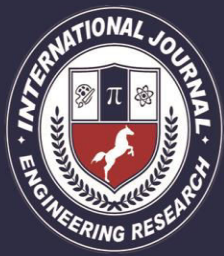
V. CONCLUSIONS

In this project work, investigate the collaborative filtering recommendation for Social networking a new perspective and present a novel typicality-based collaborative filtering recommendation method. In this method, a user is represented by a user typicality vector which can indicate the user's preference on each kind of items. A distinct feature of this method is that it selects neighbours of users by measuring user's similarity based on their typicality degrees instead of correlated items by users. Such a feature can overcome several limitations of traditional collaborative filtering methods. There are several possible future extensions to our work. In this method, we specify how to cluster resources so as to find out item groups and the corresponding user groups to form social network. With this we are going to make this application more friendly with sending request and chatting options. One possible future work is to try different

clustering methods and see how the recommendation results are affected.

REFERENCES

- [1] Z. Huang, H. Chen, and D. Zeng, "Applying Associative Retrieval Techniques to Alleviate the Sparsity Problem in Collaborative Filtering," *ACM Trans. Information Systems*, vol. 22, no. 1, pp. 116-142, 2004.
- [2] G. Adomavicius and A. Tuzhilin, "Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions," *IEEE Trans. Knowledge and Data Eng.*, vol. 17, no. 6, pp. 734-749, June 2005.
- [3] K.M. Galotti, *Cognitive Psychology In and Out of the Laboratory*, third ed. Wadsworth, 2004.
- [4] G.L. Murphy, *The Big Book of Concepts*. MIT Press, 2002.
- [5] L.W. Barsalou, *Cognitive Psychology: An Overview for Cognitive Scientists*. Lawrence Erlbaum Assoc., 1992.
- [6] S. Schiffer and S. Steele, *Cognition and Representation*. Westview Press, 1988.
- [7] D.L. Medin and E.E. Smith, "Concepts and Concept Formation," *Ann. Rev. of Psychology*, vol. 35, pp. 113- 138, 1984.
- [8] W. Vanpaemel, G. Storms, and B. Ons, "A



Varying Abstraction Model for Categorization,” Proc. Cognitive Science Conf. (CogSci '05), pp. 2277-2282, 2005.

[9] L.W. Barsalou, “Ideals, Central Tendency, and Frequency of Instantiation as Determinants of Graded Structure in Categories,

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