A User-Based Multi-Criteria Recommendation Approach for Personalized Recommendations

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***Abstract*— Recommender systems are information filtering systems designed to resolve the problem of information overload by automatically recommending items of interest to particular users based on their profiles or preferences. The user-based Collaborative Filtering (CF) techniques are very popular techniques and have been widely adopted in recommender systems. Despite their popularity, they suffer from the sparsity and new user problems, especially when insufficient rating information is available. Such limitations resulting in reduced recommendation accuracy and coverage. The addition of multi-criteria ratings besides the use of users' trust information can effectively mitigate such problems and produce more personalized recommendations. Accordingly, this paper proposes a User-based Multi-Criteria Recommendation approach that integrates the multi-criteria ratings of items and users' trust information to alleviate the abovementioned problems of user-based CF techniques. Experimental results show the significance of the proposed approach when compared with the standard user-based CF techniques in respect to the improvement of recommendation accuracy and coverage when confronted with sparsity and new user problems.**

Keywords-Recommender Systems; Multi-Criteria; Collaborative Filtering; Trust Filtering; Sparsity; New User.

I. INTRODUCTION

Recommender systems are information filtering systems developed to minimize the effect of the increasing growth of information by recommending items that are relevant to the explicit and implicit preferences of users. Items can be online information, products or services in different real-world applications such as e-commerce, e-government, e-learning, e-tourism, and e-health [1-7]. Collaborative filtering (CF) is one of the most acknowledged techniques in recommender systems for making personalized recommendations based on: 1) rating information of items that are liked by other like-minded users (user-based CF), 2) rating information of items that are similar to the items the user has liked in the past (item-based CF). User-based CF techniques have been successfully used in recommender systems for different domains. However, they may produce poor recommendations due to major limitations such as sparsity and new user problems. Sparsity is the result of the insufficient ratings of users, especially when the number of ratings obtained is very small compared to the number of ratings that must be predicted. The new users are generally defined as the users who have rated only few items [1, 8]. To overcome these problems, recommender systems have recently embarked on the incorporation of CF with additional information as a solution to the insufficient users' ratings to generate more reliable recommendations. Examples of such additional information are: the multi-criteria ratings of items [9-12], and the trust relationships among users [6, 12-14].

Most current recommender systems consider only an item's overall rating which is a single-criterion value from a user to produce recommendations. However, it has been acknowledged that a user may take into account more than one feature of an item when making the selection of a recommended item. That is, the understanding of why users like besides of what users like is very significant in producing more effective recommendations. On other words, the availability of multi-criteria ratings of items can guarantee a more advanced understanding of users' preferences (i.e. why users like such items). Thus, the incorporation of complex preferences of users in multi-criteria recommender system can accurately model preferences of each user and, hence, enhancing the performance of the recommendation accuracy [9, 13, 15, 16]. This study utilizes the multi-criteria ratings of items to better model user preferences and, therefore, produce more personalized recommendations.

Social network analysis has been recently adopted in recommender systems due to the increasing expansion of Web-based social networks. To help enhance the user experience, recommender systems increasingly utilizing users' social relationships to provide more personalized and reliable recommendations. Trust is widely accepted as a major human social relationship in social networks and online communities. In a recommender system, trust is generally defined as "how well does Alice trust Bob concerning the specific product or taste" [1]. Trust-based recommender systems exploits social networks weighted by trust ratings to generate recommendations to users based on other users they trust. Trust information can be explicitly or implicitly collected. Explicit trust information can be collected from users where each user can identify others as trustworthy or not. Whereas, implicit trust information can be derived based on users' rating information [13, 14]. This study utilizes the implicit trust information as an additional information source to better model user preferences and, therefore, produce more personalized recommendations.

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This paper proposes a User-based Multi-Criteria Recommendation approach which incorporates multi-criteria ratings of items and implicit trust relations among users to produce high-quality personalized recommendations. The proposed approach, first, uses the user-based MC CF method to produce predictions based on the user-based MC similarity among users. Then, it uses the user-based MC implicit trust filtering method to produce predictions based on the implicit trust relations between users. Finally, predictions are integrated together using the weighted harmonic mean aggregation method. The proposed approach utilizes the MC ratings of users to better model their preferences, thus, enhancing the performance of the recommendation accuracy. Whereas, the implicit trust relations among users act as an additional source of knowledge in which the inherent properties of trust and trust propagation can be exploited to overcome the lack of missing ratings, thus, help in reducing the impact of sparsity and new user problems. The remainder of this paper is organized as follows. In Section 2, the related works are reported. Section 3 describes the proposed recommendation approach, and related experiments are shown in Section 4. Finally, conclusions and future study are given in Section 5.

II. Related works

Despite the fact that single-criteria recommender systems have been successfully employed in different applications, multi-criteria rating systems are being increasingly deployed in a number of commercial sectors such as: Zagat's Guide (http://www.zagat.com/) which is a restaurant guide that provides three criteria for restaurant ratings (e.g., food, decor, and service); and Yahoo Movies (http://movies.yahoo.com) where each user can rate movies with respect to four criteria (Story, Acting, Direction, and Visuals) in addition to an overall rating. Furthermore, in academia, a number of researchers [17-24] have developed a number of multi-criteria recommender systems. Such studies acknowledged the benefits of using multi-criteria ratings in recommender systems as it can accurately model users' preferences, and therefore provide accurate recommendations.

Martin et al. [17] propose a multi-criteria recommendation algorithm to support decision makers in their activities according to their profiles. The proposed algorithm is based on automatic learning techniques and scalable scheduling solutions to allow the evolution and refining of users' profiles. Experimental results on the MovieLens dataset show the quality of the produced recommendations.

Nilashi et al. [18] propose a recommendation algorithm using Fuzzy Self-Organizing Map and Adaptive Neuro Fuzzy Inference System to improve the accuracy of multi-criteria recommender systems. To reduce the dimensionality in multi-criteria CF datasets and address the multi-collinearity problem, the Principal Component Analysis is also applied. Experimental results on TripAdvisor and Yahoo! Movies datasets demonstrate the significant improvement of the proposed algorithm in terms of recommendation accuracy.

Jhalani et al. [19] propose a linear regression based multi-criteria recommender system. The proposed system, first, utilizes a multi linear regression approach for computing the weights for various criteria. Then, it uses the weights to calculate the overall rating for each item based on the aggregation of similarities and ratings for different criteria. Experimental results performed on a Yahoo! Movies dataset confirm the feasibility of the proposed approach in outperforming other classical heuristic approaches in terms of recommendation coverage, recall and f-measure.

Shambour et al. [24] propose an Item-based Multi-Criteria Collaborative Filtering algorithm that integrates multi-criteria ratings of items and the items' semantic information to lessen current limitations of the classical item-based CF techniques, specifically, sparsity and cold item problems. Experimental evaluation on a Yahoo! Movies dataset reveal the efficiency of the proposed approach by achieving improved recommendation accuracy and more coverage when confronted with aforementioned limitations in comparison with the classical item-based CF recommendation techniques.

Parveen et al. [20] propose a multi-criteria recommender system using fuzzy based Multi-criteria decision making approach. Experimental evaluation illustrates the enhancement of the recommendation accuracy of the proposed approach in comparison with a standard multi-criteria recommendation approach. In another study, Parveen et al. [21] propose a multi-criteria recommender system using CF in addition to the genetic algorithm to leverage information extracted from multi-criteria ratings. Experimental results on a Yahoo! Movies dataset show the effectiveness of the proposed recommendation system in terms of recommendation accuracy, precision and recall.

Nilashi et al. [22] propose a multi-criteria based CF recommendation approach where customer segments are detected using Ant system-based and Ant K-means clustering algorithms. Then, preference models using regression functions are learned for each customer segment. The principal component analysis is then applied to reduce the noise in the data and recognize the most significant quality dimensions for the different customer segments. Experimental results on a Yahoo! Movies dataset demonstrate the significant improvement of the proposed method in terms of recommendation accuracy when compared to standard multi-criteria recommendation methods.

Bilge and Kaleli [23] propose an item-based multi-criteria CF framework. The proposed framework identifies the most appropriate neighborhood selection approach and investigates the predictions' accuracy performance of statistical regression-based methods. Experimental evaluation on a Yahoo! Movies dataset verifies that item-based multi-criteria CF algorithms outperforms item-based single-criteria rating CF algorithms in terms of recommendation accuracy.

III. Description of the User-based Multi-Criteria Recommendation Approach (UMCRA)

To deal with the sparsity and new user problems and improve the recommendation accuracy and coverage, this study develops a recommendation approach which incorporates multi-criteria ratings of items and implicit trust relations among users to produce high-quality personalized recommendations. It first uses the user-based MC CF method to produce predictions based on the user-based MC similarity between users. Then, it

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uses the user-based MC implicit trust filtering method to produce predictions based on the implicit trust relations between users. Finally, predictions are integrated together using the weighted harmonic mean aggregation method. The process of the proposed UMCRA is described in three main components as follows:

A. The User-based MC CF Similarity Component

In this component, for each pair of users, the user-based MC CF similarity is calculate through two steps. At first step, the user-based adjusted cosine similarity metric, as given by Eq. (1), is used to calculate the partial similarity, based on each of the rating criteria *c,* between the active user *a* and user *b.* Then, all of partial similarities (for all available criteria) are aggregated using the weighted average, as given by Eq. (2), to derive the overall user-based MC CF similarity value.

$$UPSim^{c}_{a,b} = \frac{\sum_{i=1}^{|I_a \cap I_b|} (r^{c}_{a,i} - \overline{r_i}) \times (r^{c}_{b,i} - \overline{r_i})}{\sqrt{\sum_{i=1}^{|I_a \cap I_b|} (r^{c}_{a,i} - \overline{r_i})^2} \times \sqrt{\sum_{i=1}^{|I_a \cap I_b|} (r^{c}_{b,i} - \overline{r_i})^2}}, \qquad (1)$$

where $r^{c}_{a,i}$ and $r^{c}_{b,i}$ denote the users *a* and *b* ratings on item *i* respecting criteria *c*, respectively. $\overline{r_i}$ represents the value of mean rating of all users on item *i*. $|I_a \cap I_b|$ is the amount of items that users *a* and *b* have rated in common.

$$UMCSim_{a,b} = \frac{\sum_{c=1}^{k} w_c \times UPSim^{c}_{a,b}}{\sum_{c=1}^{x} w_c}, \qquad (2)$$

where $UPSim^{c}_{a,b}$ is the partial similarity value between users *a* and *b* based on criteria *c*. w_c is a weight representing the significance of criterion *c* for the active user *a*, and *k* is the number of overall criteria.

However, Eq. (1) takes only into consideration the absolute value of ratings between users and ignores the percentage of common ratings between them. Hence, to further improve the performance of Eq. (1), the Dice coefficient [25], which takes into account the percentage of common ratings between users in computing their similarity as given by Eq.(3), is employed as a weighted function to overcome the aforementioned shortcoming of Eq. (2).

$$UDice_{a,b} = \frac{2 \times |I_a \cap I_b|}{|I_a| + |I_b|}, \qquad (3)$$

Where $|I_a|$ and $|I_b|$ are the amount of rated items of users *a* and *b*.

Formally, the final proposed user-based MC CF similarity metric between the active user *a* and user *b* is given by:

$$WSim_{a,b} = UMCSim_{a,b} \times UDice_{a,b} \qquad (4)$$

B. The User-based MC Trust Filtering Component

In this component, the user-based MC implicit trust values between each pair of users is calculate through two steps. At first step, the direct implicit trust values of every pair of users are derived based on users' ratings. Then, indirect implicit trust are propagated between not directly connected users.

1) Calculating User-based MC Direct Implict Trust

In this study, the "trustworthiness of a given user" is defined as how reliable is user *a* in delivering highly accurate recommendations to user *b* in the past [13]. Recently, it has been confirmed that there is a positive association between users similarity and trust in online communities [1, 26]. Accordingly, the trustworthiness of a given user can be computed by measuring the accuracy of predicted ratings of that user, as a recommender, in the past to the active user. For this purpose, the Resnick's prediction method [27], as given by Eq. (5), is utilized to determine the predicted rating. The predicted rating on item *i* by user *a* (having only one neighbor user *b*) is given as follows:

$$P_{a,i} = \overline{r_a} + (U^{b}(i) - \overline{r_b}), \qquad (5)$$

where $\overline{r_a}$ and $\overline{r_b}$ correspond to the mean ratings over all criteria of users *a* and *b* respectively. $U^{b}(i)$ is the overall utility (i.e., additive value function) of user *b* with respect to item *i* defined as follows:

$$U^{b}(i) = \sum_{k=1}^{x} w^{b}_{k} c^{b}_{k}(i), \; where \; \sum_{k=1}^{x} w^{b}_{k} = 1 \qquad (6)$$

where $c^{b}_{k}(i)$ corresponds to the rating value of item *i* by user *b* respecting criterion c_k and w^{b}_{k} is a weight obtained by user *b* to imply the significance of criterion c_k on item *i*. Then, the *Euclidean Distance* similarity measure [10, 23], as shown in Eq. (7), is used to calculate the user-based distance between the users *a* and *b* based on each individual criterion as shown below:

$$Dis_{a,b} = \sqrt{\sum_{i=1}^{n} abs(P_{a,i} - U^{b}(i))^2}, \qquad (7)$$

where $P_{a,i}$ corresponds to the predicted rating of user *a* on item *i*, and *n* is the total number of items that users *a* and *b* have rated in common. Note that the Max-Min Normalization method [28] has been used to normalize the values of predicted and overall utility ratings to guarantee that the value of $Dis_{a,b} \in$ [0..1]. Obviously, the smaller is the distance between two users are, the larger the direct implicit trust value between them is. Therefore, the following metric is needed to convert the resultant distance into the direct implicit trust value:

$$UTrust_{a,b} = \frac{1}{1 + Dis_{a,b}}, \qquad (8)$$

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Similar to the user-based adjusted cosine similarity metric, the Euclidean Distance takes only into consideration the absolute value of ratings between users and ignores the percentage of common ratings between them. The impact of this concern can be noticed when users with limited amount of rated items can obtain a high value of trust with the other users. Thus, to further improve the performance of Eq.(7), the Dice coefficient, as given by Eq.(3), is used again as a weighted function to overcome the aforementioned shortcoming. Formally, the final proposed user-based MC implicit trust metric between the active user *a* and user *b* is given by:

$$WTrust_{a,b} = UTrust_{a,b} \times UDice_{a,b} \tag{9}$$

2) Trust Propagation

Trust can be propagated when direct trust links do not exist among users in the trust network. That is, if user *a* trusts user *b* and user *b* trusts user *c*, it can be inferred that user *a* can trust user *c* to some extent. To enhance the exploitation of trust information, it is essential to propagate trust in order to discover more (indirectly) trusted neighbors. In this study, we adopt the trust propagation method proposed by Papagelis et al. [29] to infer the trust value of indirectly connected users. The trust propagation method makes sure that the inferred trust value is considerably weighted by the co-rated items between directly trusted users. Thus, the direct relationship which has more co-rated items is more trustworthy and involves additional weight. Formally, the propagated implicit trust value that specifies to what extent user *a* implicitly trusts user *c* is realized as follows:

$$PTrust_{a \to c} = \frac{\sum_{b \in \mathrm{adj}(a)} \left(\left|I_{a,b}\right| \times WTrust_{a,b}\right) + \left(\left|I_{b,c}\right| \times WTrust_{b,c}\right)}{\sum_{b \in \mathrm{adj}(a)} \left|I_{a,b}\right| + \left|I_{b,c}\right|}, \tag{10}$$

where user *a* has *b*s direct trusted adjacent neighbours that trust user *c*, $WTrust_{a,b}$ and $WTrust_{b,c}$ is the user-based MC implicit trust values between users *a* and *b*, *b* and *c* respectively. $|I_{a,b}|$ and $|I_{b,c}|$ are the amont of items that have been rated in common by users *a* and *b*, *b* and *c* respectively.

C. The Rating Predictions Component

This component contains two steps. Firstly, it computes the rating predictions of all unrated items for an active user using the deviation-from-mean method [30, 31]. The deviation-from-mean method is used twice, once by the user-based MC CF method, and once by the user-based MC implicit trust filtering method to produce predictions for the active user *a* on item *i*, as shown by (11) and (12) respectively.

$$P_{a,i}^{CF} = \overline{r_a} + \frac{\sum_{n=1}^{NN^{CF}} (WSim_{a,n} \times (U^n(i) - \overline{r_n}))}{\sum_{n=1}^{NN^{CF}} WSim_{a,n}}, \tag{11}$$

$$P_{a,i}^{Trust} = \overline{r_a} + \frac{\sum_{n=1}^{NN^{Trust}} (WTrust_{a,n} \times (U^n(i) - \overline{r_n}))}{\sum_{n=1}^{NN^{Trust}} WTrust_{a,n}}, \tag{12}$$

where $\overline{r_a}$ and $\overline{r_n}$ correspond to the mean ratings over all criteria of users *a* and *n* respectively. $U^n(i)$ is the overall utility of user *n* with respect to item *i*. $WSim_{a,n}$ and $WTrust_{a,n}$ referred to the user-based MC CF similarity and the user-based MC implicit trust values between users *a* and *n* respectively. NN^{CF} and NN^{Trust} are the most Nearest Neighbors of users to the active user *a* acquired based on both the user-based MC CF and implicit trust methods. Finally, an aggregation method, namely weighted harmonic mean, is applied to produce the overall predicted rating value $P_{a,i}$ as shown by Eq. (13).

$$P_{a,i} = \frac{2 \times P_{a,i}^{CF} \times P_{a,i}^{Trust}}{P_{a,i}^{CF} \times P_{a,i}^{Trust}} \tag{13}$$

IV. Experimental Evaluation

A. Dataset and Evaluation metrics

A Yahoo! Movies MC dataset (YMMC) [32] has been used to verify the performance of the proposed UMCRA. The YMMC dataset was obtained from the Yahoo! movies website (http://movies.yahoo.com). The YMMC dataset contains 34,800 rating records from 1,716 users for 965 movies, where the rating scale is from 1 to 5. The reason for using the YMMC dataset is the availability of specific ratings on four criteria: acting, story, visuals and direction of each movie. The dataset is divided into one training dataset that contains 80% of all user ratings and one testing dataset that contains the remaining 20% of ratings.

Two well-known metrics for measuring recommender systems, are statistical accuracy and coverage metrics, have been used in this study. Metrics of statistical accuracy compare between the predicted ratings with the actual ratings. The Mean Absolute Error (MAE) as the most popular statistical accuracy metric used in this study to measure the accuracy of the generated recommendations due to its simplicity and easy interpretation. Moreover, the coverage metric which can be defined as the percentage of recommended items to the total set of items is also used in this study to measure the ability of a given recommender system to generate recommendations (refer to [33] for more details on the metrics).

B. Benchmark algorithms

The results of the proposed UMCRA have been compared with the results of two commonly used user-based single-criteria CF algorithms [34]: 1) The user-based single-criteria CF based on the adjusted cosine similarity (denoted by USCCF-AVC) ; and 2) The user-based single-criteria CF based on the cosine similarity (denoted by USCCF-VC).

C. *Experimental analysis*

To demonstrate the enhancement of the proposed UMCRA, two major experiments have been carried out to compare the proposed UMCRA with the two benchmark algorithms in terms of the recommendation accuracy and coverage. The first experiment comprises a performance comparison between all algorithms when faced with different levels of sparsity. The second experiment comprises a performance comparison between all algorithms when faced with different number of ratings of new users.

1) Evaluating the Recommendation Accuracy and Coverage on the Sparsity problem. To maintain a diverse set of sparse datasets, the sparsity metric is used for this purpose. The sparsity level of any dataset is defined as 1 – (no. of overall ratings in the dataset / (no. of users × no. of items)). Consequently, six sparse datasets have been generated from the YMMC dataset in which the sparsity degree ranges from the highest of 99.8% to the lowest of 98.0 % (i.e., 99.8%, 99.5%, 99.0%, 98.8%, 98.5%, and 98.0%). Figures 1 and 2 clearly show the effectiveness of the proposed UMCRA in lessening the impact of the sparsity problem when compared with the benchmark algorithms. Figure 1 demonstrates that the MAE falls (i.e., recommendation accuracy improves), while the level of sparsity decreases. Figure 2 shows that the coverage increases (i.e., recommendation coverage improves), while the level of sparsity decreases. Both figures show the dominance of the proposed UMCRA in outperforming the other benchmark algorithms with respect to recommendation accuracy and coverage over all levels of sparsity.

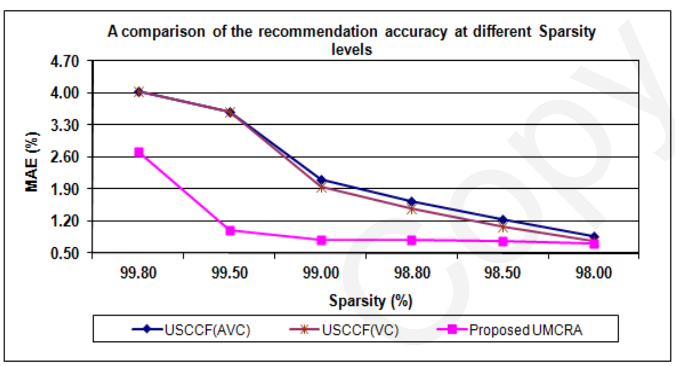

Fig. 1. A comparison of the recommendation accuracy between the proposed UMCRA with other benchmark user-based SC CF approaches on different levels of Sparsity

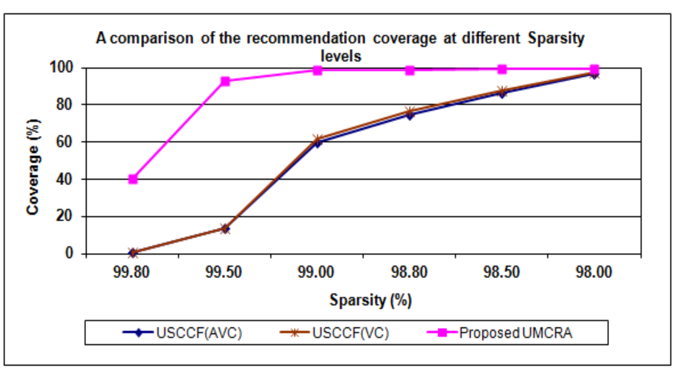

Fig. 2. A comparison of the recommendation coverage between the proposed UMCRA with other benchmark user-based SC CF approaches on different levels of Sparsity

2) Evaluating the Recommendation Accuracy and Coverage on the new user problem. The feasibility of the proposed UMCRA compared to other benchmark algorithms in improving the new user problem is assessed in this experiment. To begin, six datasets have been extracted from the YMMC dataset in which each dataset contains new users with specified number of ratings per user (from 10 to 20 ratings). Figures 3 and 4 noticeably confirm the success of the proposed UMCRA in decreasing the impact of the new user problem when compared with the benchmark algorithms. Figure 3 reveals that the MAE falls (i.e., recommendation accuracy improves), while the number of ratings for new users increases. Figure 4 shows that the coverage increases (i.e., recommendation coverage improves), while the number of ratings for new users increases. Both figures show the lead of the proposed UMCRA in outperforming the other benchmark algorithms with respect to recommendation accuracy and coverage at each number of ratings of new users.

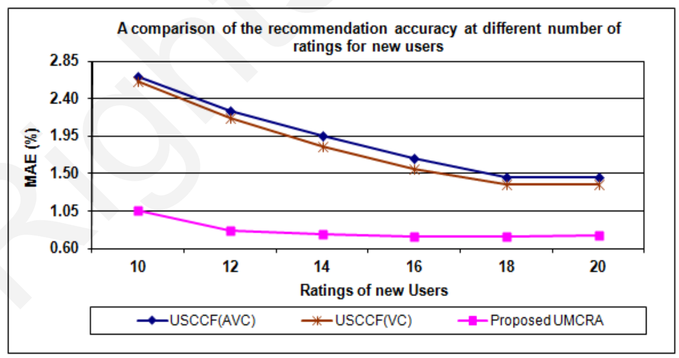

Fig. 3. A comparison of the recommendation accuracy between the proposed UMCRA with other benchmark user-based SC CF approaches on different number of ratings for new users

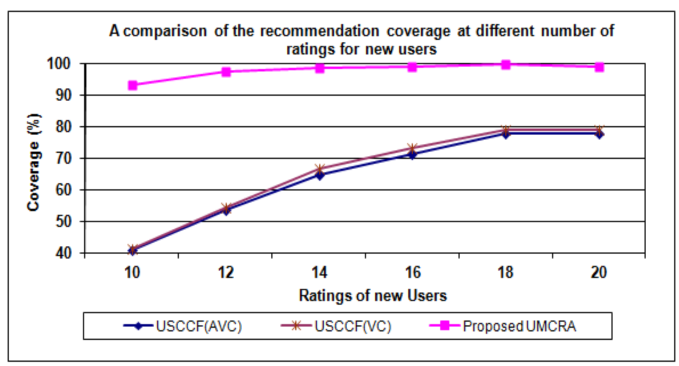

Fig. 4. A comparison of the recommendation coverage between the proposed UMCRA with other benchmark user-based SC CF approaches on different number of ratings for new users

To sum up, the proposed UMCRA has proved to be a significant enhancement in reducing the impact of the poor recommendation accuracy and coverage resulting from the sparsity and new user problems.

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V. CONCLUSIONS AND FUTURE WORK

This study proposes a User-Based Multi-Criteria Recommendation Approach (UMCRA) which combines multi-criteria ratings of items and implicit trust relations among users to produce high-quality personalized recommendations. The UMCRA utilizes the MC ratings of items to better model users' preferences, thus, enhancing the performance of the recommendation accuracy. On the other hand, the implicit trust relations among users act as an additional source of knowledge in which the instinctive properties of trust and propagation of trust are exploited to overcome the lack of missing ratings, and thus, help in reducing the impact of sparsity and new user problems. The analysis of the experimental results validate the higher performance of the proposed UMCRA compared with other benchmark user-based SC CF algorithms. The UMCRA shows its significance in overcoming the poor recommendation accuracy and coverage resulting from the sparsity and new user problems. Future study will focus on implementing the proposed UMCRA in an intelligent recommender system to be utilized in different domains of applications.

REFERENCES

[1] J. Lu, D. Wu, M. Mao *et al.*, "Recommender system application developments: A survey," *Decision Support Systems,* vol. 74, pp. 12-32, 2015.

[2] S. Fraihat, and Q. Shambour, "A Framework of Semantic Recommender System for e-Learning," *Journal of Software,* vol. 10, no. 3, pp. 317-330, 2015.

[3] Q. Shambour, and J. Lu, "A framework of hybrid recommendation system for government-to-business personalized e-services," in Proceedings of the 7th International Conference on Information Technology: New Generations (ITNG 2010), Las Vegas, Nevada, USA, 2010, pp. 592-597.

[4] J. Lu, Q. Shambour, and G. Zhang, "Recommendation technique-based government-to-business personalized e-services," in Proceedings of the Annual Meeting of the North American Fuzzy Information Processing Society (NAFIPS 2009), Cincinnati, OH, 2009, pp. 1-6.

[5] Q. Shambour, and J. Lu, "Government-to-business personalized e-services using semantic-enhanced recommender system," *EGOVIS 2011, LNCS*, K. Andersen, E. Francesconi, Å. Grönlund *et al.*, eds., pp. 197–211, Heidelberg: Springer, 2011.

[6] Q. Shambour, and J. Lu, "An effective recommender system by unifying user and item trust information for B2B applications," *Journal of Computer and System Sciences,* vol. 81, no. 7, pp. 1110-1126, 2015.

[7] L. Guo, B. Jin, C. Yao *et al.*, "Which Doctor to Trust: A Recommender System for Identifying the Right Doctors," *Journal of Medical Internet Research,* vol. 18, no. 7, pp. e186, 2016.

[8] C. C. Aggarwal, "An Introduction to Recommender Systems," *Recommender Systems: The Textbook*, pp. 1-28, Cham: Springer International Publishing, 2016.

[9] G. Adomavicius, N. Manouselis, and Y. Kwon, "Multi-Criteria Recommender Systems," *Recommender Systems Handbook,* pp. 769-803, , US: Springer, 2010.

[10] G. Adomavicius, and Y. O. Kwon, "New recommendation techniques for multicriteria rating systems," *IEEE Intelligent Systems,* vol. 22, no. 3, pp. 48-55, 2007.

[11] Q. Shambour, and J. Lu, "A hybrid multi-criteria semantic-enhanced collaborative filtering approach for personalized recommendations," in Proceedings of the 2011 IEEE/WIC/ACM International Conference on Web Intelligence (WI'11), Lyon, France, 2011, pp. 71-78.

[12] Q. Shambour, and J. Lu, "Integrating multi-criteria collaborative filtering and trust filtering for personalized recommender systems," in Proceedings of the 2011 IEEE Symposium on Computational Intelligence in Multicriteria Decision-Making (MCDM 2011), Paris, France, 2011, pp. 44-51.

[13] Q. Shambour, and J. Lu, "A hybrid trust-enhanced collaborative filtering recommendation approach for personalized government-to-business e-services," *International Journal of Intelligent Systems,* vol. 26, no. 9, pp. 814-843, 2011.

[14] C. C. Aggarwal, "Social and Trust-Centric Recommender Systems," *Recommender Systems: The Textbook*, pp. 345-384, Cham: Springer International Publishing, 2016.

[15] G. Adomavicius, and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE Transactions on Knowledge and Data Engineering,* vol. 17, no. 6, pp. 734-749, 2005.

[16] N. Manouselis, and C. Costopoulou, "Analysis and classification of multi-criteria recommender systems," *World Wide Web,* vol. 10, no. 4, pp. 415-441, 2007.

[17] A. Martin, P. Zarate, and G. Camillieri, "A Multi-Criteria Recommender System Based on Users' Profile Management," *Multiple Criteria Decision Making: Applications in Management and Engineering*, C. Zopounidis and M. Doumpos, eds., pp. 83-98, Cham: Springer International Publishing, 2017.

[18] M. Nilashi, M. Salahshour, O. Ibrahim *et al.*, "A New Method for Collaborative Filtering Recommender Systems: The Case of Yahoo! Movies and TripAdvisor Datasets," *Journal of Soft Computing and Decision Support Systems,* vol. 3, no. 5, pp. 44-46, 2016.

[19] T. Jhalani, V. Kant, and P. Dwivedi, "A Linear Regression Approach to Multi-criteria Recommender System," *Data Mining and Big Data*, Y. Tan and Y. Shi, eds., pp. 235-243, Cham: Springer International Publishing, 2016.

[20] H. Parveen, M. Ashraf, and R. Parveen, "Improving the performance of multi-criteria recommendation system using fuzzy integrated meta heuristic," in International Conference on Computing, Communication & Automation, 2015, pp. 304-308.

[21] R. Parveen, V. Kant, P. Dwivedi *et al.*, "Enhancing Recommendation Quality of a Multi Criterion Recommender System Using Genetic Algorithm," *Mining Intelligence and Knowledge Exploration*, R. Prasath, A. K. Vuppala and T. Kathirvalavakumar, eds., pp. 526-535, Cham: Springer International Publishing, 2015.

[22] M. Nilashi, D. Jannach, O. b. Ibrahim *et al.*, "Clustering- and regression-based multi-criteria collaborative filtering with incremental updates," *Information Sciences,* vol. 293, pp. 235-250, 2015.

[23] A. Bilge, and C. Kaleli, "A multi-criteria item-based collaborative filtering framework," in Proceedings of the 11th International Joint Conference on Computer Science and Software Engineering (JCSSE), Chon Buri, 2014, pp. 18-22.

[24] Q. Shambour, M. a. Hourani, and S. Fraihat, "An Item-based Multi-Criteria Collaborative Filtering Algorithm for Personalized Recommender Systems," *International Journal*

of Advanced Computer Science and Applications, vol. 7, no. 8, pp. 274-279, 2016.

[25] W. B. Frakes, and R. Baeza-Yates, *Information retrieval: data structures and algorithms*: Prentice Hall, 1992.

[26] C.-N. Ziegler, and G. Lausen, "Analyzing Correlation between Trust and User Similarity in Online Communities," *Trust Management*, C. Jensen, S. Poslad and T. Dimitrakos, eds., pp. 251-265, Berlin, Heidelberg: Springer Berlin Heidelberg, 2004.

[27] P. Resnick, N. Iacovou, M. Suchak *et al.*, “GroupLens: an open architecture for collaborative filtering of netnews,” in Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work, USA, 1994, pp. 175 - 186.

[28] J. Han, and M. Kamber, *Data mining: concepts and techniques*, Second Edition ed., San Francisco: Morgan Kaufmann, 2006.

[29] M. Papagelis, D. Plexousakis, and T. Kutsuras, "Alleviating the Sparsity Problem of Collaborative Filtering Using Trust Inferences," *Trust Management*, Lecture Notes in Computer Science P. Herrmann, V. Issarny and S. Shiu, eds., pp. 224-239, Heidelberg: Springer, 2005.

[30] J. Herlocker, J. A. Konstan, and J. Riedl, “An empirical analysis of design choices in neighborhood-based collaborative filtering algorithms,” *Information Retrieval,* vol. 5, no. 4, pp. 287-310, 2002.

[31] P. Resnick, N. Iacovou, M. Suchak *et al.*, "GroupLens: an open architecture for collaborative filtering of netnews." pp. 175 - 186.

[32] K. Alodhaibi, “Decision-guided recommenders with composite alternatives,” Information Technology, George Mason University, Virginia, 2011.

[33] C. C. Aggarwal, "Evaluating Recommender Systems," *Recommender Systems: The Textbook*, pp. 225-254, Cham: Springer International Publishing, 2016.

[34] L. Guo, and Q. Peng, “A Combinative Similarity Computing Measure for Collaborative Filtering,” in Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE 2013), Paris, France, 2013, pp. 1921-1924.

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