A Trust-Based Recommender System for Personalized Restaurants Recommendation

Original Scientific Paper

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Abstract *– Several online restaurant applications, such as TripAdvisor and Yelp, provide potential consumers with reviews and ratings based on previous customers' experiences. These reviews and ratings are considered the most important factors that determine the customer's choice of restaurants. However, the selection of a restaurant among many unknown choices is still an arduous and time-consuming task, particularly for tourists and travellers. Recommender systems utilize the ratings provided by users to assist them in selecting the best option from many options based on their preferences. In this paper, we propose a trust-based recommendation model for helping consumers select suitable restaurants in accordance with their preferences. The proposed model utilizes multi-criteria ratings of restaurants and implicit trust relationships among consumers to produce personalized restaurant recommendations. The experimental results based on a real-world restaurant dataset demonstrated the superiority of the proposed model, in terms of prediction accuracy and coverage, in overcoming the sparsity and new user problems when compared to other baseline CF-based recommendation algorithms.*

Keywords*: restaurant, collaborative filtering, recommender systems, multi-criteria, sparsity, new user*

1. INTRODUCTION

The restaurant industry has experienced a remarkable expansion in recent years, with a slew of new restaurants springing up. Consumers nowadays are more interested in trying a variety of cuisines, and just because there are many restaurants does not mean that everyone will visit each one and try everything. Moreover, the internet offers a vast amount of online restaurant review information, which is particularly useful for consumers when deciding where to dine. Consumers, on the other hand, frequently find it time-consuming and difficult to extract meaningful information from the vast amount of online information available, making selecting a restaurant even more challenging. Given how people's lifestyles are changing as a result of their use of technology, an intelligent recommender system that recommends restaurants can be a good solution for consumers to assist them in finding a restaurant that fits their needs and preferences [1-7].

Recommender systems are programs that aim to suggest the most appropriate items (services and products) to specific users by anticipating a user's interest in an item based on relevant information about the items, the users, and their interactions with the items. The goal of building recommender systems is to avoid information overload by obtaining the most relevant information from a large amount of data, allowing personalized services to be provided in various disciplines such as e-commerce, e-business, e-library, e-learning, e-tourism, e-health, and e-government [8-13]. Collaborative filtering (CF) is a well-recognized technique in recommender systems for producing personalized recommendations based on: 1) rating information of items liked by other similar users (user-based CF), and 2) rating information of items similar to items the user has liked in the past (item-based CF). User-based CF approaches have proven to be effective recommendation approaches across a variety of disciplines. However, due to major constraints such as sparsity and new user, they may provide poor recommendations (reducing accuracy) or decline recommendations (reducing coverage). Sparsity arises from a lack of user ratings, particularly when the number of ratings obtained is modest in comparison to the number of ratings that must be predicted. The term "new user" refers to a user who has only rated a very small number of items [14]. To address these issues and enhance the accuracy and coverage of user-based CF recommender systems, researchers have lately begun to utilize the multi-criteria ratings of users and combine CF with additional information, such as the trust relationships between users, to provide more trustworthy recommendations [15,16].

To generate recommendations, most current recommender systems solely consider an item's overall rating, which is a single-criterion score from a user. However, it has been established that while selecting an item, a user may consider more than one feature of the item. That is, understanding why users like things in addition to what they like is critical to making more successful recommendations. To put it another way, the exploitation of multi-criteria ratings of items can ensure a better understanding of users' preferences, hence improving recommendation accuracy [15-17]. Furthermore, numerous websites nowadays allow users to rate items based on multiple criteria. In terms of restaurants, users can rate restaurants based on a variety of aspects. On TripAdvisor (https://www.tripadvisor.com/), for example, consumers can rate restaurants based on three criteria: service, food, and value. The multi-criteria ratings of restaurants are used in this study to accurately learn consumers' preferences and, as a result, provide more personalized restaurant recommendations.

Trust-based recommender systems use social networks that are weighted by trust ratings to make recommendations to users based on other users they trust. Trust data can be gathered either explicitly or implicitly. Users' explicit trust information can be collected, and each user can determine whether or not others are trustworthy. Implicit trust information, alternatively, can be inferred from user ratings [15,16]. The implicit trust information is used in this study as a supplementary source of information to alleviate the impact of sparsity and new user drawbacks and, as a result, increase the coverage of recommendations.

To this end, in this paper, we propose a trust-based recommendation model for helping consumers select suitable restaurants in reference to their preferences. Specifically, we propose a Trust-based Multi-Criteria CF (TMCCF) recommendation model that includes multi-criteria item ratings and implicit trust relationships among users for restaurant recommendations. There are a number of advantages of the proposed recommendation model. First, the model exploits the multi-criteria ratings of restaurants to learn the users' preferences more accurately. Second, the model incorporates implicit trust information of users as an additional source of information to overcome the sparsity and new user challenges. This paper is organized as follows. Sections 2 and 3 present related work and introduce the proposed model, respectively. Experimental evaluations and results are demonstrated in Section 4. Finally, we conclude the paper and further work in Section 5.

2. RELATED WORK

Restaurants recommendation is a hot topic among numerous recommendation applications that has attracted the interest of practitioners and researchers in recommender systems in recent years [1-7]. A number of restaurant recommender systems have utilized mobile-based context aware services as well as location-based approaches, for example, Chu and Wu [1] proposed a restaurant recommender system based on mobile context aware services to supply users with personalized restaurant recommendations. The proposed system significantly satisfies the user's needs for restaurant recommendations by utilizing location-based approaches and user preferences. The experimental results of users satisfaction revealed that the proposed system satisfies the search requirements of the mobile users to a great extent. In another study, Zeng et al. [3] developed a restaurant recommendation system based on mobile environment. The proposed system employs a user preference model based on the features of user's previously visited restaurants as well as location information. The Baidu map cloud service and Baidu web cloud service were utilized to find the user's location as well as the nearby restaurants. The results of a case study revealed that the proposed system is capable of successfully recommending appropriate restaurants to a variety of users.

Some restaurant recommendation systems use CF-based approaches to provide suggestions to users. For instance, a restaurant recommendation system, based on a user-based CF approach, was developed by Li et al. [4]. The proposed approach is broken down into three components: user rating similarity, user attributes similarity, and a fusion of these similarities. The experiments were carried out on data from 627 restaurants and 46718 ratings provided by 30081 users from the dianping.com website, which covered the city of Guilin, China. Using MAE and RMSE measurements, the proposed approach is shown to be effective and accurate in recommending restaurants when compared to traditional user-based CF. In similar research, Fakhri et al. [5] propose a user-based CF method for recommending restaurants based on users' ratings and users' attributes. If a target user wants to find a restaurant, then the system will calculate the similarities between the target user and other users based on their ratings and attributes. Then neighbors who have the biggest similarity with the target user will be consulted for personalized restaurants recommendations. For validation purposes, the study uses a questionnaire of users who have rated restaurants they have visited. The dataset contains 86 restaurants from the zomato.com site and 50998 ratings from 593 users from the questionnaire. Furthermore, Tripathi and Sharma [6] propose a restaurant recommender system that employs the k-Nearest Neighbors and the multiclass support vector machine (SVM) classification algorithms. The experiment was carried out using a dataset obtained from the Yelp website. The experimental results reveal that both the user-based SVM and item-based SVM outperform the K-nearest neighbours algorithm.

With the growth in the number of users' reviews on websites and social media, sentiment analysis has become a viable method for extracting users' preferences. As a result, a number of restaurant recommendation systems have been analyzing user reviews to determine their preferences. For example, Alfarhood and Gauch [2] propose Traveltant, a social network-based restaurant recommender system that makes recommendations based on the user's preferences, the preferences of their friends, and the restaurant's overall reputation. To recommend restaurants, Traveltant mines the user's and his/her friends' interests from Facebook and retrieves the restaurants, their categories, and their reputation from Yelp. The proposed system is validated by asking volunteers to rate the recommendation results using 14 distinct models representing different combinations of factors, and the results demonstrate that personal preferences are the most important factor influencing the decision-making process when it comes to where to dine. In another study, a context-aware restaurant recommender system is proposed by Asani et al [7]. The proposed system first applies natural language processing techniques to users' comments about restaurants to extract the desired food names. After that, the names of foods retrieved from user comments are clustered and their sentiments about them are analyzed using a semantic technique. Finally, nearby restaurants that fit the user's food preferences are recommended. The proposed system is evaluated using data from comments on the TripAdvisor website. The evaluation results show that the proposed system can make highly accurate recommendations to users. KesavaDasu et al. [18] proposed a restaurant recommender system using a nearest neighbor based MapReduce approach. The top-k restaurants are retrieved based on the preference of the user's cuisine, the food price, and the distance from the customer's current location. Chen and Xia [19] proposed an approach for restaurant recommendations. In this approach, the user-based CF is integrated with the distance decay function to take into account the geographical effect on the restaurant selection. To provide just-in-time recommendations, the approach filters out restaurants that are not open according to the current time. In order to alleviate the sparsity of data, restaurants are assembled by their price tags. Experiments on the Foursquare dataset demonstrate that the approach outperforms traditional recommendation approaches. Dutta et al. [20] proposed a restaurant recommender system which predicts the rating of new restaurants based on an analysis of ratings, reviews, restaurant type, cuisines, online ordering service, demand, and availability of the restaurant. The authors utilize a RandomForestRegressor to predict the ratings of restaurants. The study uses the Zomato Bengaluru dataset to realize which features are vital to predicting the ratings of new restaurants.

However, in comparison to the massive amount of research done in recent years on other real-world applications of recommender systems, restaurant recommender systems have received less attention.

3. THE TRUST-BASED MULTI-CRITERIA CF (TMCCF) RECOMMENDATION MODEL

The proposed TMCCF model takes as input a raw matrix of user-item MC ratings, which is made up of M users' multi-criteria ratings on N items. The following four primary tasks exemplify the proposed TMCCF recommendation process, as shown in Fig. 1.

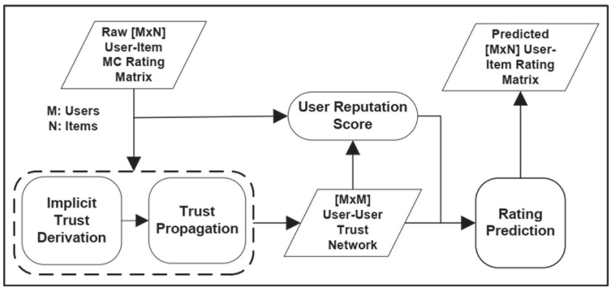

Fig. 1. The TMCCF recommendation model

3.1 THE DERIVATION OF IMPLICIT TRUST

The reliability of a given user can be obtained by appraising the accuracy of predicted ratings of that user as a recommender to the active user in the past. For this purpose, the predicted rating of user u on item i based on the only neighbor user v is given as follows:

$$P_{u,i} = \overline{r_u} + (U^v(i) - \overline{r_v}), \quad (1)$$

Where $\overline{r_u}$ and $\overline{r_v}$ denote the mean rating of users *u* and *v* respectively. $U^v(i)$ corresponds to the overall utility of user *v* on item *i* defined as follows:

$$U^v(i) = \sum_{a=1}^{k} w_a^v(i) c_a^v(i), \; where \; \sum_{a=1}^{k} w_a^v(i) = 1 \quad (2)$$

Where $c_a^v(i)$ refers to the rating value of user *v* on item *i* in respect of criterion c_a and w_a^v is a weight that implies the importance of criterion c_a by user *v* on item *i*.

Then, based on the distance between the ratings of the co-rated items and predicted ratings, and the importance of the co-rated items, a weighted version of the Euclidean distance [21] with the Inverse User Frequency measure [22] is used to compute the initial implicit similarity of users *u* and *v*.

$$wEuclidean_{u,y} = \frac{1}{1+\sqrt{\sum_{i\in I_{u,y}} \left|P_{u,i} - U^{u}(i)\right|^2}} \times Log\left(\frac{|U|}{\left|U_{i\in I_{u,y}}\right|}\right)^2 \quad (3)$$

Where $P_{u,i}$ is the rating prediction of user *u* on item *i*, and $I_{u,y}$ is co-rated item set of the users *u* and *v*. $U^u(i)$ is the overall utility of user *u* on item *i*, $|U|$ is the overall number of users in the rating matrix, and $|U_i|$ is the overall number of users who rated item *i*.

The weighted Euclidean distance, on the other hand, still has limitations as users who have rated a small number of items can gain a high level of trust with almost all other users. To solve this problem, we use the Rating Jaccard method [23]. The Rating Jaccard method is a structural similarity metric that considers the proportion of total common ratings that are equivalent in absolute value, calculated as follows:

$$RJacc_{u,y} = \frac{|N_{T(u,y)}|}{|I_u \cap I_v|} \quad (4)$$

Where $|I_u \cap I_v|$ is the total number of commonly rated items by users *u* and *v*, and *NT(u,v)* is the total number of commonly rated items that have the same absolute value given as follows:

$$N_{T(u,y)} = \begin{cases} N_{T(u,y)} + 1; & \text{if } \forall_{i\in I_u \cap I_v} R_{u,i} = R_{b,i} \\ N_{T(u,y)} \text{ remains unchanged}; & \text{otherwise} \end{cases} \quad (5)$$

In addition, to address the sparsity issue, an extreme behavior similarity metric [24] is used as a weighting factor. The extreme behavior similarity suggests that users who give an extreme rating (like 1 or 5) on the same item are more similar than users who give a neutral rating (like 3), and a user's exceptional rating on an item is more significant than the public rating.

$$ExBSim_{u,y} = \frac{\sum_{i\in I_{u,y}} S1(u_i,v_i) \times S2(u_i,v_i)}{\sqrt{\sum_{i\in I_{u,y}} S1^2(u_i,v_i)} \times \sqrt{\sum_{i\in I_{u,y}} S2^2(u_i,v_i)}} \quad (6)$$

Where *S1(*u_i*,*v_i*)* reflects the influence of users *u* and *v's* extreme ratings on item *i* compared to the median rating on the system, defined as follows:

$$S1(u_i,v_i) = \frac{1}{1+\exp(-\left|r_{u,i} - \bar{r}_{med}\right|\left|r_{v,i} - \bar{r}_{med}\right|} \quad (7)$$

Where *S2(*u_i*,*v_i*)* reflects the influence of users *u* and *v's* extreme ratings on item *i* compared to its mean rating, defined as follows:

$$S2(u_i,v_i) = \frac{1}{1+\exp(-\left|r_{u,i} - \bar{r}_i\right|\left|r_{v,i} - \bar{r}_i\right|} \quad (8)$$

Finally, the implicit trust between any given pair of users is calculated as follows:

$$iTrust_{u,y} = wEuclidean_{u,y} \times RJacc_{u,y} \times ExBSim_{u,y} \quad (9)$$

3.2 THE COMPUTATION OF TRUST PROPAGATION

Trust propagation is the notion that contributes to the formation of new trust relationships from pre-existing trust relationships. Trust transitivity is the most visible form of trust propagation, which means that if *X* trusts *Y*, and *Y* trusts *Z*, *X* will likewise trust *Z* due to transitivity. In this study, we employ trust propagation to compute the implicit trust among users who do not have direct relationships in the implicit trust social network. To compute the propagated implicit trust between users, we use the following aggregation metric.

$$pTrust_{u,h} = \frac{\sum_{v\in adj(u\,and\,h)} \left(iTrust_{u,y} \times URJacc_{u,y}\right) + \left(iTrust_{v,h} \times URJacc_{v,h}\right)}{\sum_{v\in adj(u\,and\,h)} RJacc_{u,y} + RJacc_{v,h}} \quad (10)$$

Where *adj(u and h)* is the set of trusted adjacent neighbors of user *u* who trust user *h*, which includes user *v*.

3.3 THE COMPUTATION OF USER REPUTATION SCORE

The user reputation score is used to improve the system's capacity to predict unseen items that are caused by an active user's lack of trusted nearest neighbors. It's determined based on the average variation between the user items rating and the items' mean rating, as well as the ratio of trust relationships with other users in the implicit trust social network [25], as shown below.

$$URS_u = \exp\left(-\frac{\sum_{i\in I_u} \left|r_{u,i} - \bar{r}_i\right|}{|I_u|}\right) \times \sqrt{\frac{|U_u|}{|U|}} \quad (11)$$

Where $r_{u,i}$ is the rating of user u on item *i*, $\bar{r}_i$ is the mean rating of item *i* by all users, and $|U_u|$ is the total number of users who are associated to user *u* in the implicit trust social network.

3.4 THE COMPUTATION OF RATING PREDICTION

For the computation of the final predicted rating, the deviation-from-mean metric is used, as shown below:

$$P_{u,i} = \begin{cases} \bar{r}_u + \dfrac{\sum_{v\in N^U} Trust_{u,y} \times (r_{v,i} - \bar{r}_v)}{\sum_{b\in N^U} Trust_{u,y}}; & \text{if } Trust_{u,y} \neq 0 \\ \bar{r}_u + \dfrac{\sum_{v\in N^U} URS_v \times (r_{v,i} - \bar{r}_v)}{\sum_{v\in N^U} URS_v}; & \text{if } Trust_{u,y} = 0 \end{cases} \quad (12)$$

Where $Trust_{u,y}$ represents the trust obtained from the implicit trust social network between the user *u* and neighbour user *v*, $r_{v,i}$ is the rating of item *i* by user *v*. URS_v is the user's reputation score of user *v*, and N^U is the nearest neighbour set of user *u*.

4. PERFORMANCE EVALUATION

4.1 DATASET AND EVALUATION MEASURES

The Restaurant MC dataset gathered from the TripAdvisor website is used to validate the performance of the proposed TMCCF recommendation model. The dataset comprises users' numerical ratings of restaurants on three criteria: food, service, and value. The rating values range from 1 to 5. It contains 14,633 multi-criteria ratings for 205 restaurants from 1,254 users. The dataset is split into 80% training and 20% test sets for the performance evaluation.

To measure the effectiveness of the proposed model, the recommendations made were assessed using two metrics: 1) the Mean Absolute Error (MAE) metric, which measures how much the predicted ratings are close to the actual ratings (the smaller the value of MAE, the more accurate a recommendation), and 2) the prediction Coverage metric, which is the proportion of prediction requests for which a recommendation algorithm can produce a prediction [26].

4.2 METHODS FOR COMPARISON

The results of the proposed TMCCF recommendation model were compared to the results of two commonly used benchmark user-based CF recommendation algorithms: 1) the user-based SC CF algorithm [27] that employs Pearson Correlation as a similarity measure to produce personalized recommendations (denoted by SC-UCF); and 2) the user-based MC CF algorithm [21], which adopts the similarity-based approach to produce personalized recommendations (denoted by MC-UCF).

4.3 PERFORMANCE COMPARISON

Extensive experiments have been conducted to assess the performance of the proposed TMCCF recommendation model, respecting the prediction accuracy and prediction coverage when confronted with the limitations of sparsity and new user.

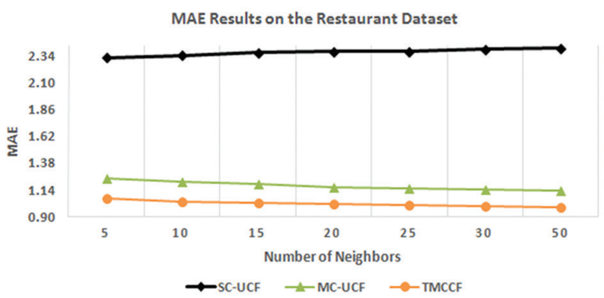

Fig. 2. MAE performance under varying numbers of neighbours on the Restauarent dataset

Performance evaluation on the Restaurant dataset. In comparison to the other benchmark algorithms on the Restaurant dataset, the proposed TMCCF model produces the best results in terms of the MAE measure under varying numbers of nearest neighbors, as shown in Fig 2. The MAE improvement results of the proposed model are roughly 57% and 13% better than the benchmark algorithms, respectively. Notably, the results illustrate that the proposed model outperforms the benchmark algorithms on the Restaurant dataset in terms of prediction accuracy.

Performance evaluation with varying Sparsity levels. A number of experiments were performed on different datasets with varying sparsity levels by filtering out users who provided ratings less than a specific number of times in the given datasets. The experimental results of the proposed TMCCF and benchmark algorithms are shown in Fig. 3 and Fig. 4. We can notice that TMCCF consistently outperforms the other benchmark algorithms in terms of MAE and Coverage in all cases. The TMCCF model obtains lower MAE values and higher Coverage percentages than the benchmark algorithms at each sparsity level, which further demonstrates that the incorporation of implicit trust information of users is very helpful in finding adequate neighbours, leading to increased prediction accuracy and coverage in highly sparse datasets.

The results demonstrate that the proposed model's MAE is improved by roughly 69% and 66%, respectively, when compared to the benchmark algorithms. Coverage has increased by around 56% and 49%, respectively. Incredibly, the proposed model outperforms benchmark algorithms in dealing with highly sparse datasets, as evidenced by the considerable improvement in MAE and Coverage results.

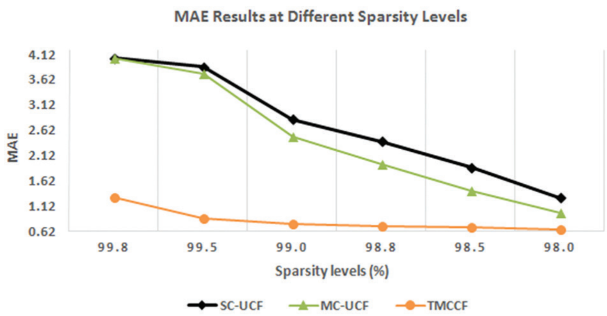

Fig. 3. MAE performance under varying levels of sparsity

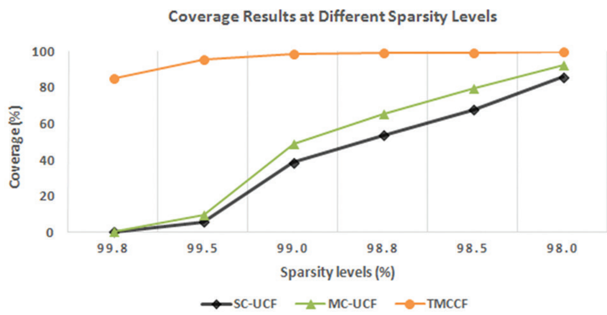

Fig. 4. Prediction coverage performance under varying levels of sparsity

Performance evaluation with a varying number of ratings of new user. A number of experiments were conducted on six datasets with a varying number of ratings of a new user (from 10 to 20 ratings) in the given datasets. Fig. 5 and Fig. 6 demonstrate the experimental results of the proposed TMCCF and benchmark algorithms. It can be noticed that TMCCF constantly exceeds the other benchmark algorithms in terms of MAE and Coverage in all cases. At each number of ratings, the TMCCF model achieves lower MAE values and higher Coverage percentages than the benchmark algorithms, which again confirms that including implicit trust information of users is very helpful in finding sufficient neighbours, resulting in increased prediction accuracy and coverage in new user situations.

When compared to the benchmark algorithms, the results demonstrate that the proposed model's MAE is improved by around 74% and 69%, respectively. Coverage has increased by around 65% and 51%, respectively. As indicated by the significant improvement in MAE and Coverage results, the proposed model outperforms benchmark algorithms in reducing the impact of the new user problem.

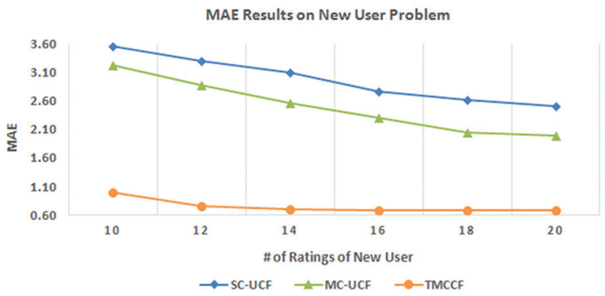

Fig. 5. MAE performance under a varying number of ratings of new users

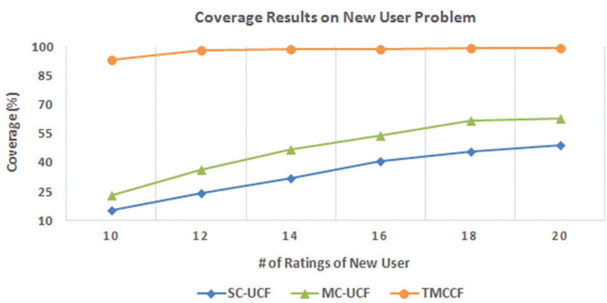

Fig. 6. Prediction coverage performance under a varying number of ratings for new users

5. CONCLUSION AND FUTURE WORK

This study proposes a trust-based recommendation model to assist consumers in selecting appropriate restaurants based on their preferences. For high-quality personalized restaurant recommendations, the proposed model utilizes multi-criteria ratings and implicit trust relationships among consumers. The proposed recommendation model has several advantages. First, the model makes use of multi-criteria restaurant ratings to better understand the consumers' preferences, resulting in improved prediction accuracy. Second, to compensate for the lack of ratings, the model exploits implicit trust information from users as an additional source of information, which improves prediction coverage by reducing the impact of sparsity and new user problems. The proposed model achieves significantly better performance as compared to benchmark CF-based recommendation algorithms in both prediction accuracy and prediction coverage. The model demonstrates its significance in overcoming the poor prediction accuracy and coverage caused by sparsity and new user issues. In the future, we will focus on analyzing the impact of incorporating other resources of information into the recommendation process, such as users' reviews of restaurants.

6. REFERENCES:

[1] C. Chu, S. Wu, "A Chinese Restaurant Recommendation System Based on Mobile Context-Aware Services", Proceedings of the 14th International Conference on Mobile Data Management, Milan, Italy, 3-6 June 2013, pp. 116-118.

[2] S. Alfarhood, S. Gauch, "Traveltant: Social Network-Based Restaurant Recommender System", Proceedings of the 14th IADIS International Conference on WWW/Internet, Maynooth, Greater Dublin, Ireland, 24-26 October 2015, pp. 47-54.

[3] J. Zeng, F. Li, H. Liu, J. Wen, S. Hirokawa, "A Restaurant Recommender System Based on User Preference and Location in Mobile Environment", Proceedings of the 5th IIAI International Congress on Advanced Applied Informatics, Kumamoto, Japan, 10-14 July 2016, pp. 55-60.

[4] L. Li, Y. Zhou, H. Xiong, C. Hu, X. Wei, "Collaborative filtering based on user attributes and user ratings for restaurant recommendation", Proceedings of the 2nd Advanced Information Technology, Electronic and Automation Control Conference, Chongqing, China, 25-26 March 2017, pp. 2592-2597.

[5] A. A. Fakhri, Z. Baizal, E. B. Setiawan, "Restaurant Recommender System Using User-Based Collaborative Filtering Approach: A Case Study at Bandung Raya Region", Proceedings of the 2nd International Conference on Data and Information Science, Bandung, Indonesia, 2019, pp. 1-7.

[6] A. Tripathi, A. K. Sharma, "Recommending Restaurants: A Collaborative Filtering Approach", Proceedings of the 8th International Conference on Reliability, Infocom Technologies and Optimization, Noida, India, 4-5 June 2020, pp. 1165-1169.

[7] E. Asani, H. Vahdat-Nejad, J. Sadri, “Restaurant recommender system based on sentiment analysis”, Machine Learning with Applications, Vol. 6, No. 2021, 2021, pp. 1-10.

[8] Q. Shambour, A. H. Hussein, M. Abualhaj, Q. Kharma, “An Effective Hybrid Content-based Collaborative Filtering Approach for Requirements Engineering”, Computer Systems Science and Engineering, Vol. 40, No. 1, 2022, pp. 113-125.

[9] Q. Y. Shambour, “Hybrid recommender systems for personalized government-to-business e-services”, University of Technology Sydney, Faculty of Engineering and Information Technology, Sydney, Australia, Phd Thesis, 2012.

[10] J. Lu, D. Wu, M. Mao, W. Wang, G. Zhang, “Recommender system application developments: A survey”, Decision Support Systems, Vol. 74, 2015, pp. 12-32.

[11] Q. Shambour, S. Fraihat, M. Hourani, “The Implementation of Mobile Technologies in Higher Education: A Mobile Application for University Course Advising”, Journal of Internet Technology, Vol. 19, No. 5, 2018, pp. 1327-1337.

[12] Q. Shambour, 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, 2015, pp. 1110-1126.

[13] S. Fraihat, Q. Shambour, “A Framework of Semantic Recommender System for e-Learning”, Journal of Software, Vol. 10, No. 3, 2015, pp. 317-330.

[14] G. Adomavicius, 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, 2005, pp. 734-749.

[15] Q. Shambour, N. Turab, O. Adwan, “An Effective e-Commerce Recommender System Based on Trust and Semantic Information”, Cybernetics and Information Technologies, Vol. 21, No. 1, 2021, pp. 103-118.

[16] Q. Shambour, “A user-based multi-criteria recommendation approach for personalized recommendations”, International Journal of Computer Science and Information Security, Vol. 14, No. 12, 2016, pp. 657-663.

[17] A. Hussein, Q. Kharma, F. Taweel, M. Abualhaj, Q. Shambour, “A Hybrid Multi-Criteria Collaborative Filtering Model for Effective Personalized Recommendations”, Intelligent Automation & Soft Computing, Vol. 31, No. 1, 2022, pp. 661-675.

[18] K. KesavaDasu, K. R. Kamal, G. Pranith, “A Cuisine Based Recommender System Using k-NN and Mapreduce Approach”, International Journal of Recent Advances in Multidisciplinary Research, Vol. 1, No. 1, 2021, pp. 9-17.

[19] L. Chen, M. Xia, “A restaurant recommendation approach with the contextual information”, Journal of Intelligent & Fuzzy Systems, Vol. 40, No. 3, 2021, pp. 4481-4489.

[20] K. B. Dutta, A. Sahu, B. Sharma, S. S. Rautaray, M. Pandey, "Machine Learning-Based Prototype for Restaurant Rating Prediction and Cuisine Selection", Advances in Intelligent Systems and Computing, Singapore, Springer, 2021, pp. 57-68.

[21] G. Adomavicius, Y. O. Kwon, “New recommendation techniques for multicriteria rating systems”, IEEE Intelligent Systems, Vol. 22, No. 3, 2007, pp. 48-55.

[22] J. S. Breese, D. Heckerman, C. Kadie, "Empirical analysis of predictive algorithms for collaborative filtering", Proceedings of the Fourteenth conference on Uncertainty in Artificial Intelligence, Madison, WI, USA, 1998, pp. 43–52.

[23] M. Ayub, M. A. Ghazanfar, T. Khan, A. Saleem, “An Effective Model for Jaccard Coefficient to Increase the Performance of Collaborative Filtering”, Arabian Journal for Science & Engineering, Vol. 45, No. 12, 2020, pp. 1-21.

[24] C. Feng, J. Liang, P. Song, Z. Wang, “A Fusion Collaborative Filtering Method for Sparse Data in Recommender Systems”, Information Sciences, Vol. 521, 2020, pp. 365-379.

[25] H. Song, Q. Pei, Y. Xiao, Z. Li, Y. Wang, "A Novel Recommendation Model Based on Trust Relations and Item Ratings in Social Networks", Proceedings of the International Conference on Networking and Network Applications, Kathmandu, Nepal, 16-19 October 2017, pp. 17-23.

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

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