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Restaurant Recommendations Based on Multi-Criteria Recommendation Algorithm

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Abstract: Recent years have witnessed a rapid explosion of online information sources about restaurants, and the selection of an appropriate restaurant has become a tedious and time-consuming task. A number of online platforms allow users to share their experiences by rating restaurants based on more than one criterion, such as food, service, and value. For online users who do not have enough information about suitable restaurants, ratings can be decisive factors when choosing a restaurant. Thus, personalized systems such as recommender systems are needed to infer the preferences of each user and then satisfy those preferences. Specifically, multi-criteria recommender systems can utilize the multi-criteria ratings of users to learn their preferences and suggest the most suitable restaurants for them to explore. Accordingly, this paper proposes an effective multi-criteria recommender algorithm for personalized restaurant recommendations. The proposed Hybrid User-Item based Multi-Criteria Collaborative Filtering algorithm exploits users' and items' implicit similarities to eliminate the sparseness of rating information. The experimental results based on three real-word datasets demonstrated the validity of the proposed algorithm concerning prediction accuracy, ranking performance, and prediction coverage, specifically, when dealing with extremely sparse datasets, in relation to other baseline CF-based recommendation algorithms.

Keywords: Recommender Systems, Restaurant, Collaborative Filtering, Multi-Criteria, Hybrid Filtering
Categories: H.3.3, H.4, M.5
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1 Introduction

With the explosive development of the Internet, e-commerce websites provide a large amount of online review information about products and services, which is very significant for consumer decision-making. For instance, if an online user plans to dine at a restaurant, to choose the best restaurant, he/she will search the internet for online reviews of restaurants and learn more about these restaurants before deciding where to dine. However, users often find it time-consuming and difficult to gain useful information from a huge amount of online information, making choosing a restaurant more difficult. Therefore, to effectively utilize such information for decision-making, it is necessary to consider the use of recommender systems due to their ability to reduce the workload of users and help them with their life-related decisions, such as assisting them in selecting a proper restaurant based on their preferences [Chu and Tsai 2017, Fu et al. 2014, Gomathi et al. 2019, Hartanto and Utama 2020, Koetphrom et al. 2018, Miao et al. 2016, Sun et al. 2015, Wang et al. 2021, Wen-ying and Guo-ming 2013].

Recent years have seen significant explosive growth in the amount of information on the World Wide Web, which provides users with a variety of choices. Recommender systems are primarily developed to address the large number of options available to users who have little experience or knowledge of handling the wide range of choices they are presented with. Recommender systems exploit various sources of information to anticipate the preferences of users for items of interest in a wide range of application domains [Shambour and Fraihat 2018, Shambour et al. 2022a, Shambour and Lu 2012, 2015, Shambour et al. 2021, Shambour 2012]. Recommendation methods have traditionally been categorized and discussed in several recent reviews [Lu et al. 2015, Lu et al. 2020]. The Collaborative Filtering (CF) recommendation method is the most widely used method in recommender systems. CF-based methods fall into two types: user-based CF and item-based CF. The main algorithm used in both methods is the nearest neighbor algorithm in which the predicted ratings of an active user on different items are calculated based on the ratings of the user's neighbors or item's neighbors. CF-based methods are widely accepted due to their easy implementation, efficiency, and ability to provide precise results. However, they are still not able to deal with the data sparsity problem. Therefore, hybrid recommender systems that fuse multiple individual filtering methods are commonly proposed to overcome such a weakness [Aggarwal 2016b].

Currently, most CF-based methods use a single rating that represents the user preference toward an item in order to generate recommendations. However, recent research works have successfully proved that the utilization of multi-criteria ratings in CF-based methods can provide better results than single criterion ratings. This is due to the fact that multi-criteria ratings can represent more sophisticated user's preferences on each item [Shambour 2016, 2021, Shambour et al. 2016]. Moreover, several websites at present allow users to rate items in multiple attributes. Specifically, when it comes to restaurants, as shown in Figures 1 and 2, users can rate restaurants based on multiple aspects. For example, on TripAdvisor, users can evaluate restaurants based on three criteria: service, food, and value. Therefore, it is necessary to develop multi-criteria based recommendation systems that can utilize the available multi-criteria ratings to fully understand users' preferences and contribute to more appropriate and valuable recommendations.

In this paper, a Hybrid User-Item based Multi-Criteria Collaborative Filtering (HUIMCCF) algorithm is proposed to help users identify proper restaurants in accordance with their preferences. It is worth noting that some aspects of this study are rather different from our previous work [Shambour et al. 2022b], which proposed a fusion-based multi-criteria CF (FBMCCF) model in the hotel recommendation domain. First, a modified version of the Triangle similarity method [Sun et al. 2017], the Relevant Jaccard method [Bag et al. 2019], and the rating preference behavior measure [Ayub et al. 2020] were incorporated into the HUIMCCF algorithm to enhance the overall implicit similarity between users. Second, a modified version of the Triangle similarity method [Sun et al. 2017] and the overlap coefficient [Verma and Aggarwal

2020] were incorporated into the HUIMCCF algorithm to efficiently measure the implicit similarity among items. Finally, the HUIMCCF algorithm is validated on additional datasets and evaluated against additional benchmark algorithms. Please refer to [Shambour et al. 2022b] for further details. The primary contributions of this study are summarized below:

- Proposing a novel hybrid algorithm that incorporates multi-criteria ratings, users' and items' implicit similarities, propagated similarity between users, and user/item reputation within an effective similarity-based MC CF framework.
- Developing a new method for measuring the implicit similarity among users that incorporates rating distance, structural similarity, and rating behavior information of users.
- Developing a new method for measuring implicit similarity among items that takes into consideration the rating distance and structural similarity information of items.
- Defining a hybrid strategy for rating prediction that takes user/item reputation into account.
- Validating the effectiveness of the proposed algorithm in terms of the prediction accuracy, ranking performance of the recommendation list, and prediction coverage using three real-world datasets: Restaurants-TripAdvisor, Hotels-TripAdvisor and Yahoo Movies. The experimental results using MAE, RMSE, nDCG, and Coverage metrics demonstrated the effectiveness of the proposed algorithm, specifically when dealing with extremely sparse datasets, when compared with other baseline CF-based recommendation algorithms.

The rest of this paper is structured as follows. In Section 2, some recent related work on the restaurant's recommender systems is reviewed. Section 3 describes the design of the proposed algorithm. The experimental evaluations and results are discussed in Section 4. Finally, Section 5 presents a concise conclusion and future work.

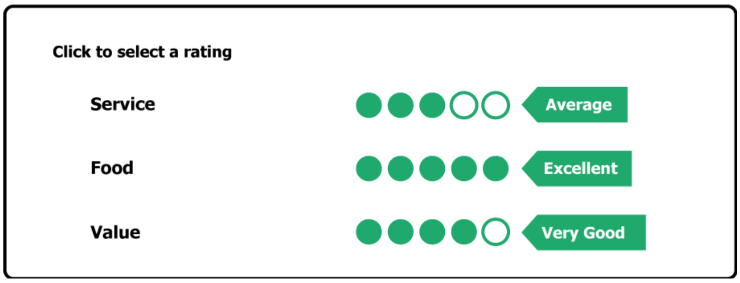

Figure 1: Example of multi-criteria rating of a restaurant on TripAdvisor

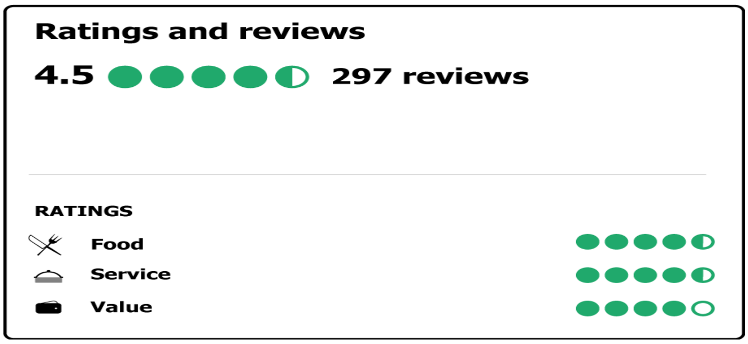

Figure 2: User multi-criteria ratings for a restaurant on TripAdvisor

2 Related Work

Among various recommendation applications, restaurant recommendation is a hot topic of growing interest to practitioners and researchers in recommender systems over the past few years [Chu and Tsai 2017, Fu et al. 2014, Gomathi et al. 2019, Hartanto and Utama 2020, Koetphrom et al. 2018, Miao et al. 2016, Sun et al. 2015, Wang et al. 2021, Wen-ying and Guo-ming 2013]. Koetphrom et al. [Koetphrom et al. 2018] conducted a comparative analysis for recommending restaurants based on content-based, CF-based, and hybrid-based filtering approaches. In content-based filtering, a regression technique that integrates attributes of users and items is used to construct a content-based prediction model. In CF-based filtering, a clustering algorithm that groups customers based on their demographic, characteristics, and personality data in addition to a cosine-based similarity approach are used to construct a CF-based prediction model. Finally, a hybrid-based approach that combines the results of the aforementioned techniques is employed to construct a hybrid-based prediction model. Experimental results illustrate that the hybrid-based filtering approach outperforms both content-based and CF-based filtering approaches. In addition to user ratings, other contexts including location data, customers' reviews, and visual information were also considered to facilitate restaurant recommendations. Wen-ying and Guo-ming [Wen-ying and Guo-ming 2013] proposed a two-stage framework for a personalized location-based restaurant recommender system in a mobile application. The proposed system provides users with effective and accurate restaurant information anywhere, anytime, based on the user's preferences and existing contextual information including the time, situation, and geographical factors. The two-stage framework contains the rule-based algorithm used in the new user phase, and the user-based in addition to the context-based CF algorithm used during the user behavior data analysis phase to modify the rule base and enhance the accuracy of recommendations. According to Sun et al. [Sun et al. 2015], the choice of a restaurant may be subjective to several factors, such as recommendations by friends, check-in locations, purchase behavior, reputation based on diverse regions, traffic conditions in the region of the restaurant, and the lively mobility behaviors of users. To take advantage of such information, the authors developed a fused matrix factorization model that exploits multi-source information, including the users' ratings, their friends' favourites, and human mobility patterns, to learn user preferences for effective restaurant recommendations. The empirical studies of the proposed model on a real-world dataset showed its effectiveness and efficiency in relation to other benchmark recommendation methods. Miao et al. [Miao et al. 2016] developed a restaurant recommendation system, namely, SI2P, using preference queries on incomplete data. The proposed system adopts the browser-server model in which the browser side offers a convenient and flexible interface for the users to interact with the system, whereas the server-side is built based on the PostgreSQL database that supports skyline and top-k dominating queries over incomplete data. For demonstration purposes, a real restaurants dataset from TripAdvisor is utilized to allow users to interact with the system and retrieve representative restaurants in an affable way. Gomathi et al. [Gomathi et al. 2019] proposed a personalized restaurant recommender system that utilizes the natural language processing technique for recommending restaurants based on users' comments. The proposed system examines the behavior of users by extracting and examining their previous comments supported by their ratings on hotels. The evaluation results show that the proposed system produced better results in terms of recommendation accuracy than other existing algorithms. Chu and Tsai [Chu and Tsai 2017] investigated the influence of utilizing visual information extracted from images published on blogs on recommending desired restaurants. The authors developed a hybrid restaurant recommender system that considers visual information by fusing the content-based and the CF approaches. The proposed hybrid system reduces the overspecialization limitation in the content-based approach by considering user preference, as well as, alleviates both the sparsity and the cold start problems in the CF approach by considering the extra visual information. The evaluation results of the proposed system confirm the effectiveness of utilizing the visual information in the recommendation of favorite restaurants. On the other hand, Wang et al. [Wang et al. 2021] proposed a restaurant recommendation system based on the prediction of traffic conditions on the internet of vehicles environment. The system adopts a two-stage learning framework. In the first stage, restaurants on the user's driving route are screened. Then, using a deep learning model, a set of restaurants based on the user attributes, restaurant attributes (including traffic conditions), and vehicle context are recommended. The experiments demonstrate that the proposed system is effective and efficient on the internet of vehicles environment. However, only a limited number of recent studies have considered the use of multi-aspect ratings of restaurants in restaurants recommender systems. For example, Fu et al. [Fu et al. 2014] proposed a hierarchical probabilistic framework to learn user preferences with multiple information fusion for effective restaurant recommendations. The proposed framework exploits the multi-aspect ratings of restaurants to discover the user preference more accurately, as well as the profile and geographic information to alleviate the geographical isolation limitation. The experimental results on a real-world restaurant dataset demonstrated the improvement of the proposed model as it outperformed other CF-based approaches in a variety of metrics, such as MAE, RMSE and NDCG. Moreover, Hartanto and Utama [Hartanto and Utama 2020] developed an intelligent decision support model to assist individual users or group of users to get recommendations for suitable restaurants based on specific parameters including customer interest, location of restaurant, price, facilities, taste, cleanliness, and status of food. The proposed model employs fuzzy logic, cosine similarity, selection, and hybrid Latin hyper-cube-hill-climbing optimization methods to generate personalized restaurants recommendations. The experimental validation involved eight customers and 75 restaurants in Jakarta.

3 The Proposed Hybrid User-Item based Multi-Criteria CF Algorithm

This section introduces the main modules of the proposed HUIMCCF algorithm that incorporates an enhanced user-based MC CF and an enhanced item-based MC CF approaches in an effective similarity-based MC CF framework [Adomavicius and Kwon 2007].

3.1 Preliminaries

Let $A = \{a_1, a_2, \ldots a_x\}$ be a set of x users, *and* $I = \{i_1, i_2, \ldots i_y\}$ be a set of y items. Let $\{c_1, c_2, \ldots, c_d\}$, be a set of criteria where an item i is rated upon, each criterion is an aspect of an item with a rating score. Therefore, the multi-criteria ratings of an item i can be then represented as a vector of d criteria $c(i) = [\, c_1(i), c_2(i), \ldots, c_d(i)]$. The overall utility U (i.e. overall rating) of item i for a user a is gained based on the Multi-Attribute Utility Theory [Dyer 2005]. The MAUT is an additive value function, defined as follows:

$$U^a(i) = \sum_{c=1}^{d} r_c^a(i) \times w_c^a(i)\ ,\ where\ \sum_{c=1}^{d} w_c^a(i) = 1 \qquad (1)$$

where $r_c^a(i)$ is the rating on criterion c of *item* i by *user* a, and $w_c^a(i)$ is the relative importance of criterion c on *item* i by *user* a that shows the user preference of criterion c.

3.2 The Architecture

The overall architecture of the proposed algorithm is presented below. The proposed algorithm consists of three main building modules: the enhanced user-based MC CF and the enhanced item-based MC CF, and the hybrid prediction modules.

A) The Enhanced User-based MC CF Module

This module is responsible for generating the user-based MC predictions using the user's similarity within the user-user implicit similarity matrix along with the user's reputation. This module is composed of four main components.

1) Direct Implicit Similarity between Users

To improve user-based MC CF prediction performance, an enhanced user-based similarity measure is proposed that takes into consideration distance, structural similarity, and rating behavior information of users.

First, the user-user direct implicit similarity is computed by utilizing the users' ratings to calculate the accuracy of the prediction of a particular user as a trusted recommender for another user. For illustration, if user b can provide precise recommendations to user a based on their historical ratings on shared items, then users a and b must attain a high implicit similarity score. Consequently, the Resnick's [22] prediction metric is used to generate a predicted rating of item i for a particular user a by exploiting only one neighbor user b.

$$P_{a,i} = \overline{r_a} + (U^b(i) - \overline{r_b}) \tag{2}$$

where $\overline{r_a}$ and $\overline{r_b}$ refer to average ratings of the users a and b, respectively. $U^b(i)$ is the overall utility (i.e. overall rating) of user b on item i.

Then, a weighted version of the Triangle similarity method [Sun et al. 2017] that considers both the length of rating vectors and the angle between them, in conjunction with the Inverse User Frequency measure [Breese et al. 1998], is employed to calculate the initial implicit similarity between users a and b.

$$UeTriSim_{a,b} = \left(1 - \frac{\sqrt{\sum_{i \in I_{a,b}} (P_{a,i} - U^a(i))^2}}{\sqrt{\sum_{i \in I_{a,b}} (P_{a,i})^2} + \sqrt{\sum_{i \in I_{a,b}} (U^a(i))^2}}\right) \times Log\left(\frac{|U|}{\left|U_{i \in I_{a,b}}\right|}\right)^2 \tag{3}$$

where $P_{a,i}$ is the rating prediction of user a on item i, and $U^a(i)$ is the overall utility of user a 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.

However, considering only the predictions error of shared items to measure user-user implicit similarity in the above metric is a trivial approach to identifying proper nearest neighbors, especially, in highly sparse datasets. Therefore, the Relevant Jaccard method [Bag et al. 2019], like an enhanced version of the Jaccard similarity method, has been used as a structural similarity measurement to consider all rating vectors of users to identify appropriate neighbors and, hence, lead to more accurate recommendations.

$$URJacc_{a,b} = \frac{1}{1 + \left(\frac{1}{|I_a \cap I_b|}\right) + \left(\frac{|I_a| - |I_a \cap I_b|}{1 + |I_a| - |I_a \cap I_b|}\right) + \left(\frac{1}{1 + |I_b| - |I_a \cap I_b|}\right)} \tag{4}$$

where $|I_a|$ is the overall number of items rated by user a, $|I_b|$ is the overall number of items rated by user b, and $|I_a \cap I_b|$ is the overall number of common items rated by users a and b.

Most recently, rating preference behavior measures [Ayub et al. 2020, Feng et al. 2020] have been applied as weighted factors while calculating similarity among users. Users tend to rate items according to their rating preferences, in which there is a type of users who rate every item low regardless of its quality, whereas, another type of users may give high ratings to each item regardless of its quality. Accordingly, a rating preference behavior measure [Ayub et al. 2020], as a function of user average and standard deviation, has been used to consider the rating pattern of users when calculating their similarity.

$$URPB_{a,b} = \cos\left(\left|\bar{r}_a - \bar{r}_b\right| \times \left|\sigma_a - \sigma_b\right|\right) \tag{5}$$

where σ_a and σ_b refer to standard deviations for ratings by users a and b, respectively.

Finally, the enhanced user-based direct implicit similarity measure for any particular pair of users is defined as:

$$iUSim_{a,b}^{Direct} = UeTriSim_{a,b} \times URJacc_{a,b} \times URPB_{a,b} \tag{6}$$

2) Propagated Implicit Similarity between Users

Bearing in mind the insufficient ratings that are commonly presented in most recommender systems, similarity propagation is necessary to derive the similarity among users who are not directly connected but are connected through mediator users. Accordingly, firstly, the calculated direct implicit similarities are utilized to form an adjacency matrix where every entry represents the level of similarity between two users. Then, an aggregation metric is exploited to derive the propagated implicit similarity between not directly connected users.

$$iUSim_{a,c}^{Prop} = \frac{\sum_{b \in intermediary\,(a\, and\, c)} \left(iUSim_{a,b} \times URJacc_{a,b}\right) + \left(iUSim_{b,c} \times URJacc_{b,c}\right)}{\sum_{b \in intermediary\,(a\, and\, c)} URJacc_{a,b} + URJacc_{b,c}} \tag{7}$$

where user b is an adjacent neighbor to users a and c, $iUSim_{a,b}$ and $iUSim_{b,c}$ are the user-based direct implicit similarity scores between users a and b, b and c, respectively. $URJacc_{a,b}$ and $URJacc_{b,c}$ are the relevant Jaccard scores between users a and b, b and c, respectively.

To sum up, the direct implicit similarity between directly connected users (i.e., users who have rated similar items) is calculated first in the user–user implicit similarity matrix using equation (6), followed by the propagated implicit similarity between not directly connected users (i.e., users who have not rated similar items) using equation (7).

3) User Reputation

The user reputation model is used to boost the system's ability to predict unseen items caused by the lacking of nearest neighbors of an active user. As shown below, it is calculated based on the average variation between his/her ratings on items and items' average, and on the proportion of connections with other *users* in the *user-user* implicit similarity matrix [Song et al. 2017].

$$UR_a = \exp\left(-\frac{\sum_{i \in I_a} \left|r_{a,i} - \bar{r}_i\right|}{\left|I_a\right|}\right) \times \sqrt{\frac{\left|U_a\right|}{\left|U\right|}} \tag{8}$$

where $r_{a,i}$ is the rating of item i by user a, $\overline{r_i}$ is the average rating of item i, and $|U_a|$ is the overall number of users who are linked to user a in the user-user implicit similarity matrix.

4) User-based MC Prediction

In this component, the deviation-from-mean approach [Herlocker et al. 2002] is employed to predict the rating of unseen item i for the active user a, as given below:

$$P^U_{a,i} = \begin{cases} \overline{r}_a + \dfrac{\sum_{b \in N^U} iUSim_{a,b} \times (r_{b,i} - \overline{r}_b)}{\sum_{b \in N^U} iUSim_{a,b}}; & \text{if } iUSim_{a,b} \neq 0 \\ \overline{r}_a + \dfrac{\sum_{b \in N^U} UR_b \times (r_{b,i} - \overline{r}_b)}{\sum_{b \in N^U} UR_b}; & \text{if } iUSim_{a,b} = 0 \end{cases} \tag{9}$$

where $r_{b,i}$ is the rating of item i by user b, UR_b is the user reputation of user b, and N^U is the set of *Top-k* nearest neighbors of user a. $iUSim_{a,b}$ denotes the implicit similarity value between users a and b, and is obtained from the user–user implicit similarity matrix.

B) The Enhanced Item-based MC CF Module

This module is responsible for generating the item-based MC predictions using items' similarity within the item-item implicit similarity matrix together with the item's reputation. This module is composed of three main components.

1) Implicit Similarity between Items

To improve item-based MC CF prediction performance, an enhanced item-based similarity measure is proposed, that takes into consideration distance and structural similarity information of items.

Mainly, the direct item-item implicit similarity is computed by utilizing items' ratings to calculate the accuracy of the prediction of a certain item as a reliable recommender to a different item. For instance, if item j can provide precise recommendations to item i based on their historical ratings on co-rated users, then items i and j must gain a high implicit similarity score. Hence, the Resnick's prediction metric is once more employed to predict the rating of item i for the active user a, by exploiting only one neighbor item j.

$$P_{a,i} = \overline{r_i} + (U^a(i) - \overline{r_j}) \tag{10}$$

where $\overline{r_i}$ and $\overline{r_j}$ refer to average ratings of the items i and j, respectively. $U^a(i)$ is the overall utility (*i*.e. overall rating) of user a on item i.

Afterward, a weighted version of the Triangle similarity method [Sun et al. 2017] combined with the Inverse Item Frequency measure [Breese et al. 1998], is used to determine the initial implicit similarity of items *i* and *j*, as below:

$$IeTriSim_{i,j} = \left(1 - \frac{\sqrt{\sum_{a \in U_{i,j}} (P_{a,i} - U^a(i))^2}}{\sqrt{\sum_{a \in U_{i,j}} (P_{a,i})^2} + \sqrt{\sum_{a \in U_{i,j}} (U^a(i))^2}}\right) \times Log\left(\frac{|I|}{\left|I_{a \in U_{i,j}}\right|}\right)^2 \tag{11}$$

where $|I|$ is the overall number of items in the rating matrix, and $|I_a|$ is the overall number of items in the profile of user *a*.

To lessen the shortcoming of considering only the predictions error of co-rated users to measure item-item implicit similarity in the above metric, the overlap coefficient [Verma and Aggarwal 2020] is used as a structural similarity measurement to consider the ratio of the intersection size of the of total common users who rated both items to the smaller of the two sets of total users who rated either items. The more common users rated both items, the higher the level of similarity between the two items.

$$IOC_{i,j} = \frac{|U_i \cap U_j|}{\min\left(|U_i|, |U_j|\right)} \tag{12}$$

where $|U_i \cap U_j|$ is the overall number of users who rate items *i* and *j*, $|U_i|$ and $|U_j|$ are the overall numbers of users who rated items *i* and *j*, respectively.

Finally, the enhanced item-based implicit similarity measure for any given pair of items is formulated as:

$$iISim_{i,j} = IeTriSim_{i,j} \times IOC_{i,j} \tag{13}$$

2) Item Reputation

The item reputation model is used to boost the system's ability to predict unseen items because of the inadequate nearest neighbors of a target item. It is calculated based on the average variation of its ratings, and on the proportion of connections with other items in the *item-item* implicit similarity matrix as specified below:

$$IR_i = \exp\left(-\frac{\sum_{a \in U_i} |r_{a,i} - \bar{r}_a|}{|U_i|}\right) \times \sqrt{\frac{|I_i|}{|I|}} \tag{14}$$

where $|I_i|$ is the overall number of items that are linked to item *i* in the item-item similarity matrix.

3) Item-based MC Prediction

In this component, the deviation-from-mean approach [Herlocker et al. 2002] is used to predict the rating of unseen item *i* for the active user *a*, as shown below:

$$P^{I}_{a,i} = \begin{cases} \overline{r}_i + \dfrac{\sum_{j \in N^I} iISim_{i,j} \times (r_{a,j} - \overline{r}_j)}{\sum_{y \in N^I} iISim_{i,j}} & ; \quad \text{if } iISim_{i,j} \neq 0 \\ \overline{r}_i + \dfrac{\sum_{j \in N^I} IR_j \times (r_{a,j} - \overline{r}_j)}{\sum_{j \in N^I} IR_j} & ; \quad \text{if } iISim_{i,j} = 0 \end{cases} \tag{15}$$

where $iISim_{i,j}$ is the item-based implicit similarity score between items i and j, where $r_{a,j}$ is the rating of item j by user a, IR_j is the item reputation of item j, and N^I is the set of *Top-k* nearest neighbors of target item i.

C) The Hybrid Prediction Module

Hybridization of multiple recommendation approaches has been shown to achieve the best performance in rating prediction. For that reason, the switch hybridization strategy [Burke 2007] is exploited to switch the recommendation approach according to certain conditions. The criterion for choosing a recommendation approach is the approach's ability to produce predicted ratings for unseen items. If both approaches can produce a predicted ratings for unseen items, then the harmonic mean metric is used to combine the predicted ratings. The harmonic mean has the advantage of being robust to substantial variances between the inputs, so that a high predicted rating will only be obtained if both predicted rating scores are high. It is noteworthy that the harmonic mean has been widely used in the literature of recommendation systems for information integration purposes [Barzegar Nozari and Koohi 2021, Bedi and Sharma 2012, Ghavipour and Meybodi 2019, Guo et al. 2015, Neve and Palomares 2020, Richa et al. 2022].

$$P_{a,i} = \begin{cases} 0 & ; \quad \text{if } P^U_{a,i} = 0 \text{ and } P^I_{a,i} = 0 \\ P^U_{a,i} & ; \quad \text{if } P^U_{a,i} \neq 0 \text{ and } P^I_{a,i} = 0 \\ P^I_{a,i} & ; \quad \text{if } P^U_{a,i} = 0 \text{ and } P^I_{a,i} \neq 0 \\ \dfrac{2 \times P^U_{a,i} \times P^I_{a,i}}{P^U_{a,i} + P^I_{a,i}} & ; \quad \text{if } P^U_{a,i} \neq 0 \text{ and } P^I_{a,i} \neq 0 \end{cases} \tag{16}$$

where $P^U_{a,i}$ and $P^I_{a,i}$ are the enhanced user-based and the item-based MC predicted ratings of user a on item i, respectively.

4 Experiments

In this section, three real-world MC datasets in addition to various evaluation measures have been exploited to perform a number of experiments to verify the validity of the proposed recommendation algorithm in comparison with other baseline recommendation algorithms.

4.1 Datasets

Three real-world MC datasets are utilized in the experiments to compare the proposed algorithm with the other baseline algorithms: the Restaurants-TripAdvisor MC dataset, the Hotels-TripAdvisor MC dataset [Jannach et al. 2014], and the Yahoo! Movies MC dataset [Alodhaibi 2011].

(1) The Restaurants-TripAdvisor MC dataset is obtained from the TripAdvisor website, and it contains numerical ratings of users in the range of 1 to 5 about restaurants on three criteria: food, service, and value. The Restaurant-TripAdvisor dataset includes 14,633 multi-criteria ratings of 1,254 users on 205 restaurants.

(2) The Hotels-TripAdvisor MC dataset consists of the MC ratings of the users in the numerical range from 1 to 5 about hotels. There are 1039 users in the TripAdvisor dataset who rated 693 hotels. Moreover, the TripAdvisor dataset includes 28,829 multi-criteria ratings on seven criteria: quality of rooms, value for money, cleanliness of the hotel, location of the hotel, overall quality of services, quality of check-in and quality of business services.

(3) The Yahoo! Movies MC dataset consists of the MC ratings of the users in the numerical range from 1 to 5 about movies. There are 1716 users in the Yahoo! Movies dataset who rated 965 movies. Additionally, the Yahoo! Movies dataset includes 34,800 multi-criteria ratings on four criteria includes acting, story, visuals, and direction.

The sparsity levels of the Restaurants-TripAdvisor, Hotels-TripAdvisor, and Yahoo! Movies datasets were 94.3%, 96%, and 93.7% respectively. A hold-out cross-validation method is used to validate the experimental results. Through cross-validation, each dataset is split into two groups: a training set and a test set. The training set includes 80% of the data, and the test set only includes 20% of the data.

4.2 Baseline algorithms

The proposed algorithm is compared with four baselines CF-based algorithms, which were revealed to be valuable methods in the literature on recommender systems.

(1) The single-criteria item-based CF algorithm (SC-ICF), which is also a standard approach in item-based recommender systems that uses Pearson Correlation as a similarity measure between items to form the neighborhood of an item and generate personalized recommendations [Deshpande and Karypis 2004].

(2) The multi-criteria user-based CF algorithm (MC-UCF) [Adomavicius and Kwon 2007], which adopts the similarity-based approach to incorporate and leverage multi-criteria rating between users to improve recommendation accuracy.

(3) The multi-criteria item-based CF algorithm (MC-ICF) [Adomavicius and Kwon 2007], which adopts the similarity-based approach to incorporate and leverage multi-criteria rating between items to improve recommendation accuracy.

(4) The multi-criteria user-item based CF algorithm (MC-UICF), which is a hybridization of the above MC-UCF and MC-ICF approaches. This method incorporates user-user similarities and item-item similarities in the recommendation process to enhance the prediction accuracy.

(5) The multi-criteria user-based CF algorithm (MC-MDCF) [Wasid and Ali 2018], which incorporates the multi-criteria ratings and uses the Mahalanobis distance method between users to provide accuracte recommendations.

(6) The multi-criteria user-based trust-enhanced CF algorithm (MC-TeCF) [Shambour 2016], which utilizes multi-criteria ratings and implicit trust relations among users to enhance the performance of the prediction accuracy and help reduce the impact of data sparsity.

4.3 Evaluation metrics

Four evaluation metrics are applied to validate the performance of the proposed algorithm with the other baseline recommendation algorithms. These metrics include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), the Normalized Discounted Cumulative Gain (nDCG), and prediction Coverage.

A prediction engine, at the base of recommender systems, is responsible of predicting user's ratings on specific items. A fundamental assumption in a recommender system is that the user will prefer a system that makes more accurate predictions. Accordingly, prediction accuracy metrics are by far the most fundamental and discussed measures in the recommendation system literature [Aggarwal 2016a, Gunawardana and Shani 2015]. In view of that, two well-known metrics for prediction accuracy, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), are employed in this study to measure the predictive accuracy of the proposed and benchmark recommendation methods. The advantage of utilizing RMSE over MAE is that it gives greater weight to large errors because they are squared before being averaged. Both metrics measure how much the predicted rating is close to the actual rating. The lower the values of MAE and RMSE are, the higher the achieved predictive accuracy is.

When the number of top-n recommended items is large, users place more emphasis on the first items on the list of recommendations. The errors made in these items are more serious than the errors made in the last items on the list. The nDCG ranking measure takes this into account, as positions are discounted logarithmically [Aggarwal 2016a]. It is used to assess the quality of the ranks in the top-n recommendation list.

In addition, the prediction coverage is considered by means of the Coverage metric, which is the proportion of predicted ratings to all the ratings in the test dataset. It is computed as the percentage of prediction requests for which the recommendation method is able to provide a prediction [Aggarwal 2016a]. Let $|I_{test}|$ be the overall number of items in the test dataset and $|P_{test}|$ be the overall number of items for which a prediction can be made in the test dataset, the *coverage* is calculated as follows:

$$Coverage = \frac{|P_{test}|}{|I_{test}|} \tag{17}$$

An important fact is that higher sparsity leads to reduced recommendation accuracy and coverage as the recommendation method becomes unable to generate recommendations for many items, as a result of not finding proper nearest neighbors, due to the small percentage of users' ratings to the total number of available items.

4.4 Results and discussion

A set of experiments have been performed to demonstrate the validity of the proposed algorithm compared with the baseline algorithms. Firstly, comparison results of the proposed algorithm against the baseline algorithms on the three MC datasets in terms of MAE, RMSE, nDCG, and Coverage are presented. Then, comparison results of the proposed algorithm against the baseline algorithms on a number of datasets with varying levels of sparsity with regard to MAE, RMSE, nDCG, and Coverage are illustrated.

4.4.1 Evaluation of prediction accuracy

The experimental results of the MAE, RMSE, nDCG, and Coverage measures are demonstrated in Figures 3–14 for the Restaurants-TripAdvisor, Hotels-TripAdvisor, and Yahoo Movies! datasets. In the Restaurants-TripAdvisor dataset, as exemplified by Figures 3–6, the proposed HUIMCCF algorithm achieves excellent results in terms of the MAE, RMSE, nDCG, and Coverage measures at various sizes of nearest neighbors (5, 10, 15, 20, 30, and 50) in comparison with the SC-ICF, MC-UCF, MC-ICF, MC-UICF, MC-MDCF, and MC-TeCF baseline algorithms. According to the average results of MAE, the enhancement results of the proposed algorithm compared with the baseline algorithms are approximately improved by 27%, 15%, 8%, 5%, 8%, and 3%, respectively. While the RMSE enhancement results are approximately improved by 29%, 19%, 9%, 6%, 5%, and 3%, respectively. It should be mentioned that the MAE and RMSE decrease with the increasing size of neighbors, in which the best achieved results have been reached with 50 nearest neighbors. Remarkably, the results confirm that the proposed algorithm surpasses the baseline algorithms with regard to the prediction accuracy. Besides MAE and RMSE, the proposed HUIMCCF algorithm shows fair improvement in terms of the average results of nDCG and Coverage. The percentages of improvements that the proposed algorithm achieved over the baseline algorithms with respect to the nDCG are almost 9%, 8%, 6%, 6%, 6%, and 5%, respectively. The percentages of improvements in terms of Coverage for the proposed algorithm in comparison with the baseline algorithms are almost 8%, 5%, 1%, 0.5%, 2%, and 0.3%, respectively. The results show that the proposed algorithm outperforms the baseline algorithms in terms of ranking performance and prediction coverage. In summary, the proposed HUIMCCF algorithm outperforms all other baseline recommendation algorithms in terms of all evaluation metrics on the Restaurants-TripAdvisor dataset.

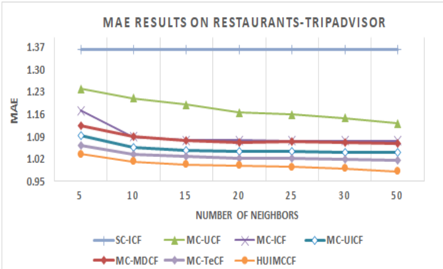

Figure 3: Results of MAE on Restaurants-TripAdvisor dataset

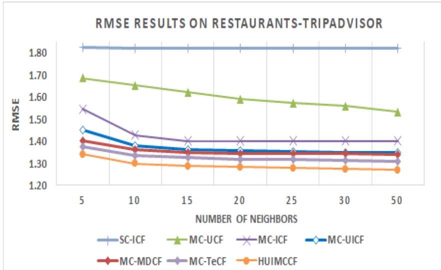

Figure 4: Results of RMSE on Restaurants-TripAdvisor dataset

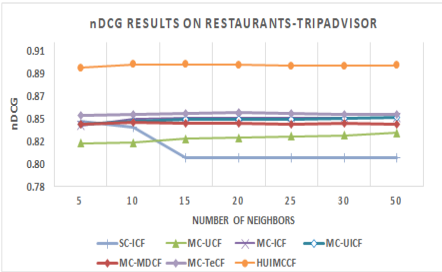

Figure 5: Results of nDCG on Restaurants-TripAdvisor dataset

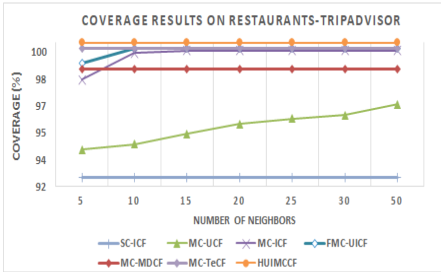

Figure 6: Results of Coverage on Restaurants-TripAdvisor dataset

With respect to the Hotels-TripAdvisor dataset, as illustrated in Figures 7–10, the proposed HUIMCCF algorithm achieves excellent results in terms of MAE, RMSE, nDCG, and Coverage measures at various sizes of nearest neighbors when compared to the SC-ICF, MC-UCF, MC-ICF, MC-UICF, MC-MDCF, and MC-TeCF baseline algorithms. When comparing the proposed algorithm's MAE average results to those of the baseline algorithms, the proposed algorithm's results are approximately enhanced by 47%, 40%, 30%, 18%, 24%, and 14%, respectively. While the average results of the RMSE are approximately improved by 46%, 42%, 30%, 19%, 21%, and 7%, respectively. The results are remarkable in that they confirm that the proposed algorithm outperforms the baseline algorithms in terms of prediction accuracy. Along with considerable improvements in MAE and RMSE, the proposed HUIMCCF algorithm also shows improvements with respect to the average results of nDCG and Coverage. The proposed algorithm improves the nDCG by almost 10%, 9%, 7%, 7%, 5%, and 4%, respectively, over the baseline algorithms. Similarly, the proposed algorithm yields Coverage improvements of almost 14%, 11%, 3%, 2%, 2%, and 0.25%, respectively, in comparison to the baseline algorithms. Thus, the results demonstrate that the proposed algorithm outperforms the baseline algorithms in terms of the ranking performance of recommendation list and prediction coverage. In conclusion, the proposed HUIMCCF method surpasses all other baseline recommendation algorithms on the Hotels-TripAdvisor dataset in terms of all evaluation metrics.

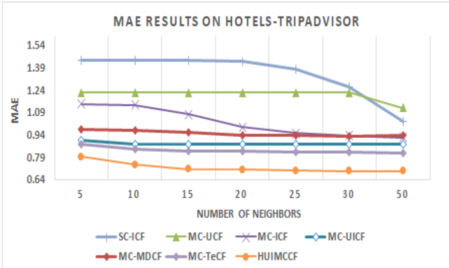

Figure 7: Results of MAE on Hotels-TripAdvisor dataset

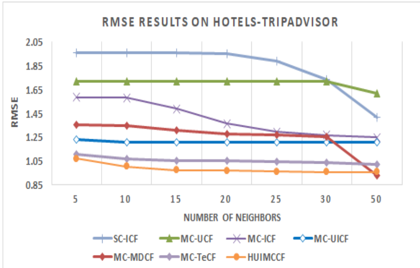

Figure 8: Results of RMSE on Hotels-TripAdvisor dataset

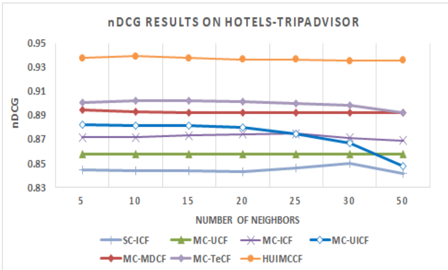

Figure 9: Results of nDCG on Hotels-TripAdvisor dataset

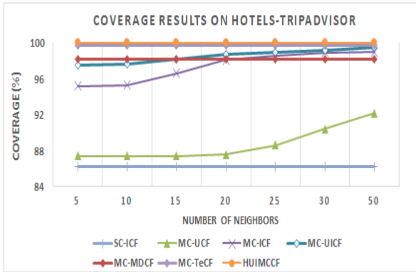

Figure 10: Results of Coverage on Hotels-TripAdvisor dataset

Finally, Figures 11–14 also reveal the competitive performance of the proposed HUIMCCF algorithm in relation to the SC-ICF, MC-UCF, MC-ICF, MC-UICF, MC-MDCF, and MC-TeCF baseline algorithms regarding MAE, RMSE, nDCG, and Coverage measures for all sizes of nearest neighbors on the Yahoo Movies! dataset. When the proposed algorithm's MAE enhancement results are compared to those of the baseline algorithms, the proposed algorithm's results are approximately enhanced by 36%, 25%, 19%, 12%, 25%, and 11%, respectively. While the results of the RMSE enhancement are approximately enhanced by 35%, 28%, 23%, 14%, 25%, and 10%, correspondingly. The results are noteworthy in that they demonstrate that the proposed algorithm surpasses baseline techniques in terms of prediction accuracy. Along with significant improvements in MAE and RMSE, the proposed HUIMCCF algorithm boosts nDCG and Coverage scores. The proposed algorithm improves the nDCG by approximately 7%, 6%, 6%, 4%, 4%, and 3%, respectively, over the baseline algorithms. Equivalently, the proposed algorithm improves coverage by about 7%, 4%, 3%, 2%, 3%, and 0.15%, respectively, when compared to the baseline algorithms. Thus, the results reveal that the proposed algorithm outperforms the baseline algorithms in terms of ranking performance and prediction coverage. To summarize, the proposed HUIMCCF algorithm outperforms all other baseline recommendation algorithms on the Yahoo Movies! dataset across all the evaluation metrics.

To sum up, all experiments demonstrate that all multi-criteria recommendation algorithms outperform the SC-ICF algorithm, which does not take multi-criteria ratings into account. The MC-UICF achieves better performance than the MC-UCF, MC-ICF, MC-MDCF in most experiments since it is a hybrid algorithm that combines MC user-based and MC item-based approaches to complement each other and improve its performance. Although the MC-TeCF algorithm makes use of implicit trust relations between users to improve prediction accuracy and mitigate the effect of sparsity, the proposed HUIMCCF algorithm outperforms the MC-TeCF algorithm in all experiments by utilizing users' and items' implicit similarities, propagated similarity between users, and user/item reputation. Finally, the best performance of the proposed HUIMCCF algorithm was achieved when the Hotels-TripAdvisor dataset was used. This is because it is sparser than the other datasets (refer to Section 4.1). This observation demonstrates the effectiveness of the proposed algorithm on sparse datasets. The following experiments will go into this topic in further depth.

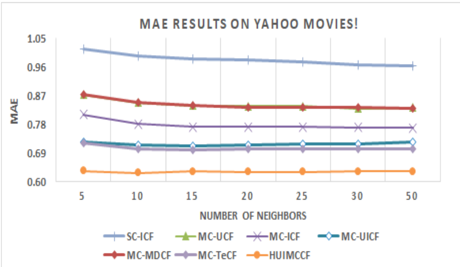

Figure 11: Results of MAE on Yahoo Movies! dataset

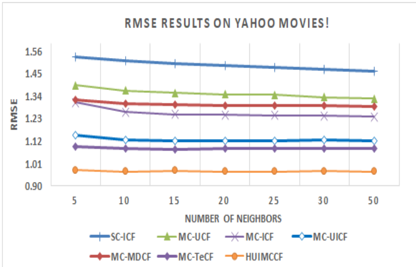

Figure 12: Results of RMSE on Yahoo Movies! dataset

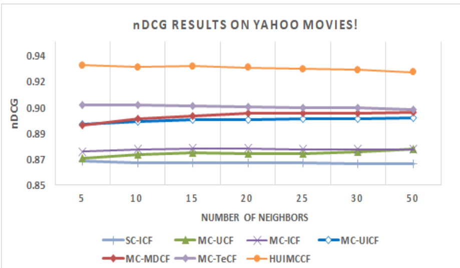

Figure 13: Results of nDCG on Yahoo Movies! dataset

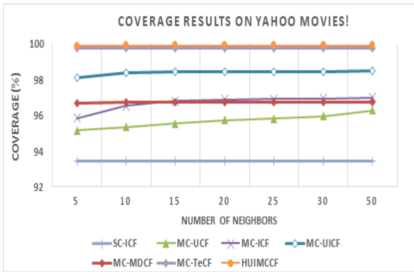

Figure 14: Results of Coverage on Yahoo Movies! dataset

4.4.2 Evaluation based on different levels of sparsity

A number of experiments are carried out to demonstrate the proposed HUIMCCF algorithm's efficacy in mitigating the data sparsity problem. To maintain different levels of sparsity, we utilized the sparsity metric to randomly remove certain ratings from the Yahoo Movies! dataset to create six sparse datasets with varying sparsity levels (i.e., 99.8%, 99.5%, 99%, 98.8%, 98.5%, and 98.0%).

The performance of the proposed HUIMCCF algorithm in relation to the SC-ICF, MC-UCF, MC-ICF, MC-UICF, MC-MDCF, and MC-TeCF baseline algorithms with reference to MAE, RMSE, nDCG, and Coverage measures at various levels of sparsity is demonstrated in Figures 15–18. The MAE average results of the proposed algorithm compared with the baseline algorithms are approximately improved by 69%, 66%, 63%, 61%, 65%, and 33%, respectively. Furthermore, the RMSE average results are approximately improved by 61%, 58%, 55%, 52%, 57%, and 23%, respectively. The results are significant in that they show that the proposed algorithm outperforms baseline approaches in terms of prediction accuracy. Along with considerable MAE and RMSE improvements, the proposed HUIMCCF algorithm significantly improves nDCG and Coverage scores. The proposed algorithm improves the nDCG by roughly 49%, 46%, 38%, 35%, 44%, and 6% over the baseline algorithms, respectively. In a similar manner, when compared to baseline algorithms, the proposed algorithm improves coverage by approximately 57%, 49%, 45%, 39%, 47%, and 10%, respectively. Thus, the proposed algorithm outperforms baseline algorithms in terms of ranking performance of the recommendation list and prediction coverage. It can be shown that the MAE and RMSE increase with increasing levels of sparsity, and the nDCG and Coverage increase with decreasing levels of sparsity. In particular, the significant improvements in MAE, RMSE, nDCG, and Coverage results indicate that the proposed algorithm is more robust and effective than other baseline algorithms in handling very sparse datasets. In particular, in the 99.8% sparse dataset, the average percentage improvements of the proposed HUIMCCF algorithm over the baseline algorithms in terms of MAE, RMSE, nDCG, and Coverage are 66%, 54%, 92%, and 89%, respectively.

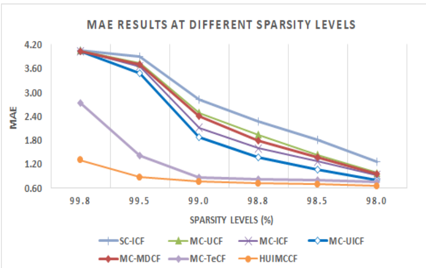

Figure 15: Results of MAE at varied levels of sparsity

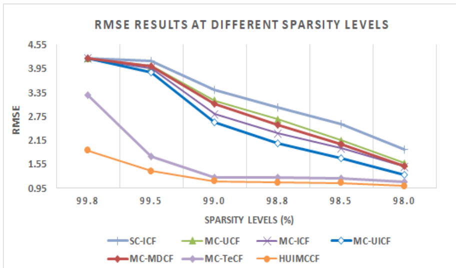

Figure 16: Results of RMSE at varied levels of sparsity

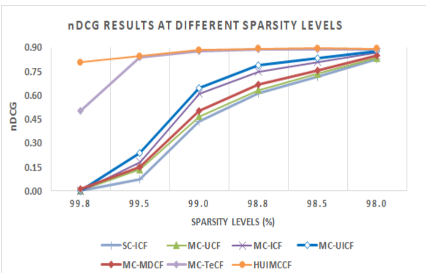

Figure 17: Results of nDCG at varied levels of sparsity

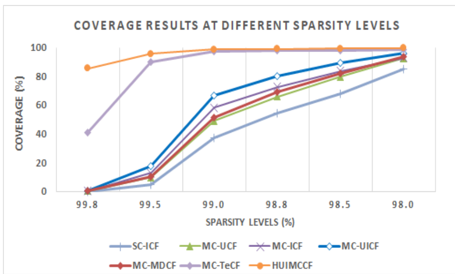

Figure 18: Results of Coverage at varied levels of sparsity

5 Conclusions and Future Work

This paper proposes an effective restaurant recommender system to help users identify proper restaurants in accordance with their preferences. The proposed algorithm uses multi-criteria ratings, users' and items' implicit similarities, propagated similarity between users, and user/item reputation to eliminate the sparseness of rating information. The prediction accuracy, ranking performance of the recommendation list and prediction coverage of the proposed algorithm are assessed on three real-world datasets: Restaurants-TripAdvisor, Hotels-TripAdvisor and Yahoo Movies. The proposed algorithm was evaluated using MAE, RMSE, nDCG, and Coverage metrics. The experimental results on all datasets demonstrated the effectiveness of the proposed algorithm with respect to prediction accuracy, ranking performance and prediction coverage, specifically, when dealing with extremely sparse datasets, when compared with other baseline CF-based recommendation algorithms.

For future work, we are interested in extending the proposed algorithm by incorporating additional information resources into the recommendation process and verifying its impact on the quality of recommendations. Additional information can be users' reviews of restaurants and other contextual information such as time of year and weather. Furthermore, an important aspect that can be studied in the future is the impact of the proposed algorithm on sparsity related issues, such as the cold start problem.

References

[Adomavicius, G.,Kwon, Y. O. 2007] Adomavicius, G.,Kwon, Y. O.:"New recommendation techniques for multicriteria rating systems"; IEEE Intelligent Systems, 22, 3 (2007), 48-55.

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

[Aggarwal, C. C. 2016b] Aggarwal, C. C.:"Neighborhood-Based Collaborative Filtering"; Recommender Systems: The Textbook; 29-70; Springer International Publishing, 2016b.

[Ayub, M.,Ghazanfar, M. A.,Khan, T.,Saleem, A. 2020] Ayub, M.,Ghazanfar, M. A.,Khan, T.,Saleem, A.:"An Effective Model for Jaccard Coefficient to Increase the Performance of Collaborative Filtering"; Arabian Journal for Science & Engineering, 45, 12 (2020), 9997–10017.

[Bag, S.,Kumar, S. K.,Tiwari, M. K. 2019] Bag, S.,Kumar, S. K.,Tiwari, M. K.:"An efficient recommendation generation using relevant Jaccard similarity"; Information Sciences, 483, 2019 (2019), 53-64.

[Barzegar Nozari, R.,Koohi, H. 2021] Barzegar Nozari, R.,Koohi, H.:"Novel implicit-trust-network-based recommendation methodology"; Expert Systems with Applications, 186, 2021 (2021), 115709.

[Bedi, P.,Sharma, R. 2012] Bedi, P.,Sharma, R.:"Trust based recommender system using ant colony for trust computation"; Expert Systems with Applications, 39, 1 (2012), 1183-1190.

[Breese, J. S.,Heckerman, D.,Kadie, C. 1998] Breese, J. S.,Heckerman, D.,Kadie, C.:"Empirical analysis of predictive algorithms for collaborative filtering", *Proc.* Proceedings of the Fourteenth conference on Uncertainty in Artificial Intelligence, Morgan Kaufmann Publishers Inc., Madison, Wisconsin (1998), 43–52.

[Burke, R. 2007] Burke, R.:"Hybrid Web Recommender Systems"; The Adaptive Web: Methods and Strategies of Web Personalization; 377-408; Springer Berlin Heidelberg, 2007.

[Chu, W.-T.,Tsai, Y.-L. 2017] Chu, W.-T.,Tsai, Y.-L.:"A hybrid recommendation system considering visual information for predicting favorite restaurants"; World Wide Web, 20, 6 (2017), 1313-1331.

[Deshpande, M.,Karypis, G. 2004] Deshpande, M.,Karypis, G.:"Item-based top-N recommendation algorithms"; ACM Transactions on Information Systems, 22, 1 (2004), 143-177.

[Dyer, J. S. 2005] Dyer, J. S.:"MAUT — Multiattribute Utility Theory"; Multiple Criteria Decision Analysis: State of the Art Surveys; 265-292; Springer New York, 2005.

[Feng, C.,Liang, J.,Song, P.,Wang, Z. 2020] Feng, C.,Liang, J.,Song, P.,Wang, Z.:"A fusion collaborative filtering method for sparse data in recommender systems"; Information Sciences, 521, 2020 (2020), 365-379.

[Fu, Y.,Liu, B.,Ge, Y.,Yao, Z.,Xiong, H. 2014] Fu, Y.,Liu, B.,Ge, Y.,Yao, Z.,Xiong, H.:"User Preference Learning with Multiple Information Fusion for Restaurant Recommendation", *Proc.* Proceedings of the 2014 SIAM International Conference on Data Mining (SDM), Philadelphia, USA (2014), 470-478.

[Ghavipour, M.,Meybodi, M. R. 2019] Ghavipour, M.,Meybodi, M. R.:"Stochastic trust network enriched by similarity relations to enhance trust-aware recommendations"; Applied Intelligence, 49, 2 (2019), 435-448.

[Gomathi, R. M.,Ajitha, P.,Krishna, G. H. S.,Pranay, I. H. 2019] Gomathi, R. M.,Ajitha, P.,Krishna, G. H. S.,Pranay, I. H.:"Restaurant Recommendation System for User Preference and Services Based on Rating and Amenities", *Proc.* 2019 International Conference on Computational Intelligence in Data Science (ICCIDS), IEEE, Chennai, India (2019), 1-6.

[Gunawardana, A.,Shani, G. 2015] Gunawardana, A.,Shani, G.:"Evaluating Recommender Systems"; Recommender Systems Handbook; 265-308; Springer US, 2015.

[Guo, G.,Zhang, J.,Yorke-Smith, N. 2015] Guo, G.,Zhang, J.,Yorke-Smith, N.:"Leveraging multiviews of trust and similarity to enhance clustering-based recommender systems"; Knowledge-Based Systems, 74, (2015), 14-27.

[Hartanto, M.,Utama, D. N. 2020] Hartanto, M.,Utama, D. N.:"Intelligent decision support model for recommending restaurant"; Cogent Engineering, 7, 1 (2020), 1-12.

[Herlocker, J.,Konstan, J. A.,Riedl, J. 2002] Herlocker, J.,Konstan, J. A.,Riedl, J.:"An empirical analysis of design choices in neighborhood-based collaborative filtering algorithms"; Information Retrieval, 5, 4 (2002), 287-310.

[Jannach, D.,Zanker, M.,Fuchs, M. 2014] Jannach, D.,Zanker, M.,Fuchs, M.:"Leveraging multi-criteria customer feedback for satisfaction analysis and improved recommendations"; Information Technology & Tourism, 14, 2 (2014), 119-149.

[Koetphrom, N.,Charusangvittaya, P.,Sutivong, D. 2018] Koetphrom, N.,Charusangvittaya, P.,Sutivong, D.:"Comparing Filtering Techniques in Restaurant Recommendation System", *Proc.* 2018 2nd International Conference on Engineering Innovation (ICEI), IEEE, Bangkok, Thailand (2018), 46-51.

[Lu, J.,Wu, D.,Mao, M.,Wang, W.,Zhang, G. 2015] Lu, J.,Wu, D.,Mao, M.,Wang, W.,Zhang, G.:"Recommender system application developments: A survey"; Decision Support Systems, 74, (2015), 12-32.

[Lu, J.,Zhang, G.-q.,Zhang, Q. 2020] Lu, J.,Zhang, G.-q.,Zhang, Q.:"Recommender Systems: Advanced Developments"; World Scientific (2020).

[Miao, X.,Gao, Y.,Chen, G.,Cui, H.,Guo, C.,Pan, W. 2016] Miao, X.,Gao, Y.,Chen, G.,Cui, H.,Guo, C.,Pan, W.:"Si^{2}p: a restaurant recommendation system using preference queries over incomplete information"; Proc. VLDB Endow., 9, 13 (2016), 1509–1512.

[Neve, J.,Palomares, I. 2020] Neve, J.,Palomares, I.:"Hybrid Reciprocal Recommender Systems: Integrating Item-to-User Principles in Reciprocal Recommendation"; Companion Proceedings of the Web Conference 2020; 848–853; Association for Computing Machinery, 2020.

[Richa,Sharma, C.,Bedi, P. 2022] Richa,Sharma, C., Bedi, P.:"Explanation-Based Serendipitous Recommender System (EBSRS)", *Proc.* Springer Singapore, Singapore (2022), 1-18.

[Shambour, Q. 2016] Shambour, Q.:"A user-based multi-criteria recommendation approach for personalized recommendations"; International Journal of Computer Science and Information Security, 14, 12 (2016), 657-663.

[Shambour, Q. 2021] Shambour, Q.:"A deep learning based algorithm for multi-criteria recommender systems"; Knowledge-Based Systems, 211, 2021 (2021), 1-8.

[Shambour, Q.,Fraihat, S. 2018] Shambour, Q., Fraihat, S.:"The Implementation of Mobile Technologies in Higher Education: A Mobile Application for University Course Advising"; Journal of Internet Technology, 19, 5 (2018), 1327-1337.

[Shambour, Q.,Hourani, M.,Fraihat, S. 2016] Shambour, Q.,Hourani, M.,Fraihat, S.:"An Item-based Multi-Criteria Collaborative Filtering Algorithm for Personalized Recommender Systems"; International Journal of Advanced Computer Science and Applications, 7, 8 (2016), 274-279.

[Shambour, Q.,Hussein, A. H.,Abualhaj, M.,Kharma, Q. 2022a] Shambour, Q.,Hussein, A. H.,Abualhaj, M.,Kharma, Q.:"An Effective Hybrid Content-based Collaborative Filtering Approach for Requirements Engineering"; Computer Systems Science and Engineering, 40, 1 (2022a), 113–125.

[Shambour, Q., Lu, J. 2012] Shambour, Q.,Lu, J.:"A trust-semantic fusion-based recommendation approach for e-business applications"; Decision Support Systems, 54, 1 (2012), 768-780.

[Shambour, Q., Lu, J. 2015] Shambour, Q.,Lu, J.:"An effective recommender system by unifying user and item trust information for B2B applications"; Journal of Computer and System Sciences, 81, 7 (2015), 1110-1126.

[Shambour, Q., Turab, N., Adwan, O. 2021] Shambour, Q.,Turab, N.,Adwan, O.:"An Effective e-Commerce Recommender System Based on Trust and Semantic Information"; Cybernetics and Information Technologies, 21, 1 (2021), 103-118.

[Shambour, Q. Y., Abu-Shareha, A. A., Abualhaj, M. M. 2022b] Shambour, Q. Y.,Abu-Shareha, A. A.,Abualhaj, M. M.:"A Hotel Recommender System Based on Multi-Criteria Collaborative Filtering"; Information Technology and Control, 51, 2 (2022b), 390-402.

[Song, H., Pei, Q., Xiao, Y., Li, Z., Wang, Y. 2017] Song, H.,Pei, Q.,Xiao, Y.,Li, Z.,Wang, Y.:"A Novel Recommendation Model Based on Trust Relations and Item Ratings in Social Networks", *Proc.* 2017 International Conference on Networking and Network Applications (NaNA), IEEE, Kathmandu, Nepal (2017), 17-23.

[Sun, J., Xiong, Y., Zhu, Y., Liu, J., Guan, C., Xiong, H. 2015] Sun, J.,Xiong, Y.,Zhu, Y.,Liu, J.,Guan, C.,Xiong, H.:"Multi-source Information Fusion for Personalized Restaurant Recommendation", *Proc.* Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, Association for Computing Machinery, Santiago, Chile (2015), 983–986.

[Sun, S.-B., Zhang, Z.-H., Dong, X.-L., Zhang, H.-R., Li, T.-J., Zhang, L., Min, F. 2017] Sun, S.-B.,Zhang, Z.-H.,Dong, X.-L.,Zhang, H.-R.,Li, T.-J.,Zhang, L.,Min, F.:"Integrating Triangle and Jaccard similarities for recommendation"; PloS one, 12, 8 (2017), 1-16.

[Verma, V., Aggarwal, R. K. 2020] Verma, V.,Aggarwal, R. K.:"A comparative analysis of similarity measures akin to the Jaccard index in collaborative recommendations: empirical and theoretical perspective"; Social Network Analysis and Mining, 10, 43 (2020), 1-16.

[Wang, Z., Liu, J., Shen, S., Li, M. 2021] Wang, Z.,Liu, J.,Shen, S.,Li, M.:"Restaurant Recommendation in Vehicle Context Based on Prediction of Traffic Conditions"; International Journal of Pattern Recognition and Artificial Intelligence, 35, 10 (2021), 1-21.

[Wasid, M., Ali, R. 2018] Wasid, M.,Ali, R.:"An improved recommender system based on multi-criteria clustering approach"; Procedia Computer Science, 131, (2018), 93-101.

[Wen-ying, Z., Guo-ming, Q. 2013] Wen-ying, Z.,Guo-ming, Q.:"A new framework of a personalized location-based restaurant recommendation system in mobile application", *Proc.* 2013 International Conference on Management Science and Engineering 20th Annual Conference Proceedings, IEEE, Harbin, China (2013), 166-172.