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A Hotel Recommender System Based on Multi-Criteria Collaborative Filtering

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Recommendation systems have lately gained popularity in a variety of applications due to their ability to operate as information filters, thus delivering useful suggestions to users based on the processing of a variety of information from various sources. The tourism industry, on the other hand, is becoming increasingly popular, with significant growth in the usage of online services for hotel selection and reservation. Potential travelers may, however, find that using such online services is inconvenient and time-consuming. This paper aims to develop a novel fusion-based multi-criteria collaborative filtering model that provides more effective and personalized hotel recommendations. The proposed model enhances the prediction accuracy of hotel recommendations by the deployment of multi-criteria ratings that precisely express travelers' complex preferences and addresses the insufficiency of rating information in the hotel domain by the exploitation of the users' and items' implicit similarity, users' similarity propagation, and user/item reputation concepts. The experimental results demonstrate that the proposed model provides higher recommendation accuracy and coverage compared to other benchmark recommendation algorithms.

KEYWORDS: Hotel Recommendations, Recommender Systems, Collaborative Filtering, Multi-Criteria, Data Sparsity.

1. Introduction

With the rapid expansion of the Internet, e-commerce websites offer a vast amount of online evaluation information about services and products. Such information has become a significant foundation for effective consumer decision-making. In particular, the reputation of a hotel is now heavily influenced by the ratings offered by its guests. In fact, guests are encouraged to review hotels and provide ratings on various aspects of the hotels. When it comes to online hotel bookings, hotel ratings have become an important factor in hotel selection. For example, when travelers plan a trip and need to book accommodation, they will browse the guests' online ratings on popular tourism websites, such as Tripadvisor.com, Agoda.com, and Expedia.com, to learn more about the accommodation hotels in order to choose the best one. However, travelers commonly find it difficult to obtain valuable information from a plethora of online evaluations, making decision-making even more complex. As a result, an effective recommendation system that acts as a decision-making system can be utilized in order to make effective use of online rating information on specific hotel features for decision-making [10, 14, 35].

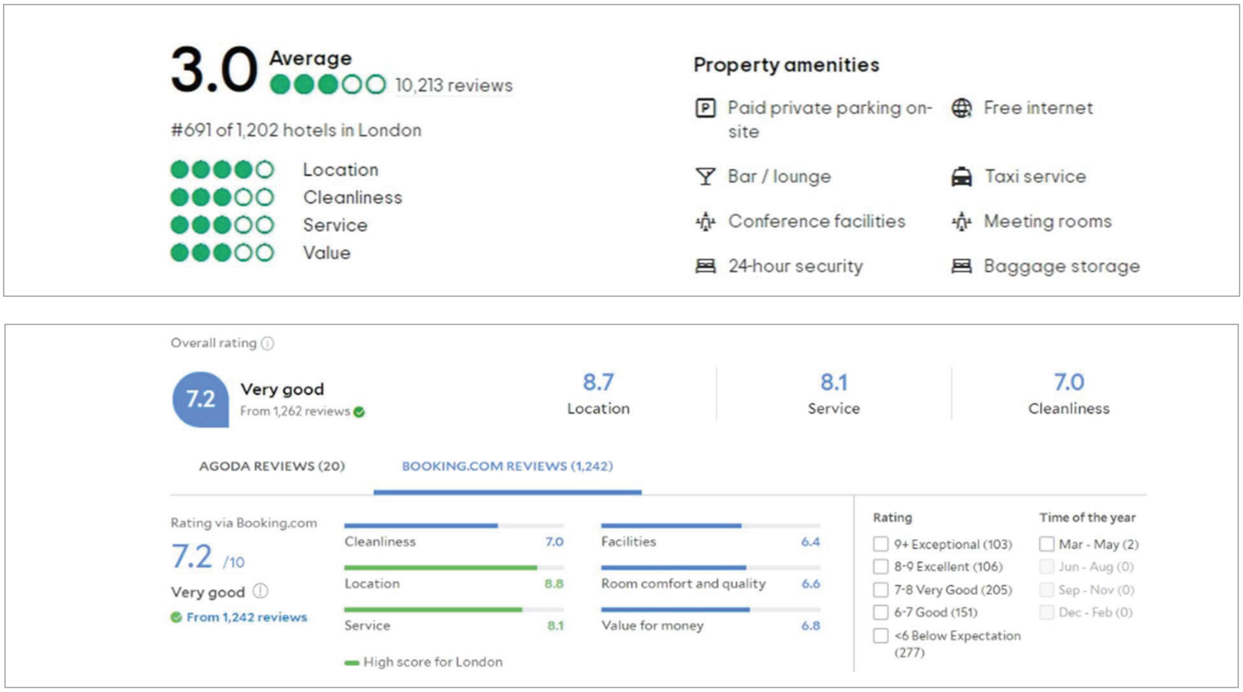
Recommendation systems are decision support systems that assist a user in deciding and selecting appropriate items. They play a very important role in reducing the problem of information overload by obtaining the most relevant information and services from a massive amount of data, allowing personalized services. They are used to filter information from various sources and predict the output based on related information about the users, the items, and the interactions between them. These systems have been increasingly popular for a variety of real-world applications in e-government, e-commerce, e-business, e-learning, e-library, e-tourism, and e-health [21, 25, 27-30]. Neighborhood-based Collaborative Filtering (CF) approaches, also referred to as memory-based approaches, were among the earliest algorithms developed for recommender systems. These approaches are based on the fact that alike users will demonstrate similar behavior in rating and alike items should receive similar ratings. Essentially, there are two types of neighborhood-based CF approaches: user-based CF and item-based CF approaches. In the user-based CF approach, the ratings provided by similar users of an active user are used to generate recommendations for him/her. In the item-based CF approach, the ratings provided by an active user are used to generate recommendations for him/her [5]. Moreover, neighborhood-based CF methods face various limitations because of data sparsity. This is due to the fact that users typically rate only a small number of available items, meaning that each pair of users or items may often have a small number of common ratings. Therefore, it becomes unlikely to successfully locate k-nearest neighbors, which affects the performance and accuracy of the neighborhood-based CF approaches [3]. In fact, the hotel domain suffers from a higher data sparsity than other recommendation domains and therefore, traditional CF approaches cannot be applied to such data [6, 33]. Accordingly, this study utilizes users' and items' implicit similarity, users' similarity propagation, and user/item reputation concepts not only to enhance the prediction accuracy, but also to address the data sparseness challenge in this domain.

A multi-criteria recommender system (MCRS) is an extension of a single-rating recommender system in which users provide ratings on a number of criteria for each item. Despite the fact that an overall rating of an item provides information about how much the user likes the item, multi-criteria ratings provide more insights about why the user likes it. Accordingly, multi-criteria ratings facilitate a more accurate estimation of the similarity between user-user or item-item similarities [2, 24, 26]. The selection of a hotel is greatly influenced by multiple criteria such as location, cleanliness, facilities, and service. Figure 1 depicts an example of a hotel's overall ratings on two different hotel booking websites. Consequently, the design and development of multi-criteria recommender systems that can leverage extra rating information, properly grasp user preferences, and contribute to more accurate and effective hotel recommendations have become essential. In terms of the recommendation process, multi-criteria based CF can deliver more accurate hotel recommendations by taking into account the knowledge of crucial aspects that lead travelers to select an appropriate hotel that matches their preferences.

In the hotel domain, various studies have been carried out recently on hotel recommendations. One of the ways to recommend a hotel is by considering the

Figure 1

Examples of the multi-criteria ratings of a specific hotel on two different hotel booking websites (Tripadvisor.com and Agoda.com)



overall explicit ratings provided by guests. From these studies, Zhang et al. [33] proposed a novel hotel recommendation hybrid framework by combining latent factor models with a content-based method. Lee et al. [20] combine term-frequency k-nearest neighbor, a content-based method, and a popularity measure to recommend hotels to users that they would like to reserve. Chen et al. [11] proposed a hotel recommender system that uses item-based CF and user location. However, due to the inherent sparsity problem in the hotel recommendation domain, using explicit rating information is not always practical [6, 33]. Furthermore, traditional single overall ratings are unable to adequately capture the diverse preferences of travelers, as different travelers have varying preferences for aspects of their preferred hotel. Some may pay attention to facilities, while others may pay more attention to location or service quality. Other methods proposed in the literature for hotel recommendations are based on hotel reviews. From the studies concerning those, Zhang and Morimoto [34] proposed a hotel recommendation system based on the sentiments of review comments. Abbasi et al. [1] coupled natural language processing and a supervised classification approach to assess sentiments and extract implicit features from several hotel reviews. Forhad et al. [14] introduced a hotel recommendation framework that analyzes customer reviews and local hotel amenities to make recommendations. Nevertheless, hotel reviews are not always available, and processing reviews is a demanding natural language processing activity that requires time and effort from all involved parties [19].

To this end, the novelty of this study can be summarized as below:

1 We understand that when it comes to hotel selection, various travelers will have different needs and preferences. At present, hotel websites such as Tripadvisor.com, Agoda.com, and Expedia.com, among others, are not highly interactive with travelers, leaving them as platforms that contain only hotel information without providing any personalized services. Nonetheless, this research offers a solution to the problem of matching travelers with hotels. Hence, the proposed work will be of great value in hotel industry personalization research since it will make it easier for hotel websites to

transition to a new stage, enabling them to provide personalized hotel recommendations to travelers.

2 It proposes a fusion-based multi-criteria CF (FB-MCCF) model that fuses an enhanced user-based CF and an enhanced item-based CF approaches. The proposed model 1) uses multi-criteria ratings to precisely express travelers' complex preferences, thus enhancing the prediction accuracy of hotel recommendations; and 2) exploits the users' and items' implicit similarity, users' similarity propagation, and user/item reputation concepts in order to address the sparsity challenge that is caused by the insufficiency of rating information in the hotel domain [6, 33], with no need for any external information from other information sources.

3 The experimental results on a real-world hotel MC dataset show that the proposed model attains effective results when compared with a number of existing recommendation approaches with respect to predictive accuracy and coverage, particularly when dealing with sparse data. This ascertains the applicability of the proposed recommendation model in the hotel recommendation domain since it attains a better successful recommendation rate.

The organization of this paper is as follows. Section 2 provides a brief overview of related work in the domain of hotel recommendations. Section 3 presents the detailed methodology for developing the proposed model, while Section 4 presents the experimental results. Section 5 concludes the study.

2. Related Works

Studies on hotel recommendation systems have attracted the attention of scholars. The studies can be classified into two classes: The first class includes the hotel recommendation systems that utilize numerical rating information. The second class comprises the hotel recommendation systems that utilize text review information [1, 11, 12, 14, 18, 20, 33-36].

Zhang et al. [33] proposed a novel hotel recommendation hybrid framework by combining latent factor models with a content-based method. The proposed framework improves the prediction accuracy by overcoming the sparsity and cold-start challenges inherent in the hotel recommendation domain. Experiments conducted on the Ctrip dataset prove the effectiveness of the proposed framework by outperforming other latent factor recommendation models. Lee et al. [20] proposed a hybrid recommender system for hotel recommendations. The proposed system combines term-frequency k-nearest neighbor, a content-based method, and a popularity measure, as well as utilizes implicit profiles of users and items to recommend hotels to users that they like to reserve. Experimental results on a hotel reservation dataset show the performance improvement of the proposed recommender system over two state-of-the-art recommendation methods. Zhang and Morimoto [34] proposed a hotel recommendation system that uses implicit ratings for hotels based on the sentiments of review comments. First, the proposed system uses Latent Dirichlet Allocation to analyze texts in comments and automatically extract representative topics regarding hotels. Then, for each hotel, texts are analyzed to discover the sentiment for each extracted topic. Experiments using a dataset from TripAdvisor show that the proposed system works effectively for hotel recommendations and outperforms traditional CF-based techniques. In order to improve prediction accuracy, Abbasi et al. [1] designed a recommendation method based on consumers' explicit and implicit preferences. The proposed method coupled sentiment analysis with the CF with the matrix factorization method as a deep learning approach. To assess sentiments and extract implicit features, the proposed method employs natural language processing and a supervised classification approach. Experiments using a dataset from iranhotel.com show that the proposed method improves CF performance. Forhad et al. [14] introduced a hotel recommendation framework that analyzes customer reviews and local hotel amenities to make recommendations. First, the system calculates scores based on the reviews of the hotel booking datasets. The hotel's review scores are then combined with the scores for the surrounding environment. Finally, the hotels are ranked based on their final aggregated scores. To assess the usefulness of the proposed framework, experiments were conducted utilizing datasets from online hotel booking platforms such as TripAdvisor and Booking. Experimental results verify the effectiveness of the proposed recommendation framework. Chen et al. [11] proposed a hotel recommender system that uses item-based collaborative filtering and user location.

It counts the hotels that travelers have never stayed in and predicts how much they could enjoy them using hotel similarity. Furthermore, this study considers the hotel's functionality and examines the three criteria that consumers value the most: services, prices, and facilities. Chen [12] developed a hotel recommendation system that groups travelers based on the variations in their decision-making mechanisms rather than their characteristics. Travelers are split into several clusters, with each cluster exhibiting similar decision-making behaviors. Consequently, the proposed system employs a variety of strategies to recommend appropriate hotels to travelers in distinct clusters. A regional experiment was undertaken in Hsinchu City, Taiwan, to examine the effectiveness of the proposed system. The results show that the successful recommendation rate of the proposed system outperformed three other recommendation approaches. Kaya [18] proposed a hotel recommendation system based on a link prediction method that takes into account the customer's location information. A customer hotel bipartite network was first created, and the relationship information in this network was then used as data. After that, a supervised link prediction algorithm that takes into account the location of customers was presented. The proposed method overcomes other state-of-the-art recommendation approaches, according to the experimental results carried out on a dataset from TripAdvisor. Zhong et al. [36] proposed a hotel recommendation approach to enhance the quality of hotel recommendations and assist travelers in finding hotels that meet their preferences on Tripadvisor. To alleviate the challenges in multi criteria ratings, the authors generate a comprehensive score by clustering users with diverse preferences into distinct groups using the K-means algorithm. According to a case study based on a dataset from Tripadvisor.com, the proposed recommendation approach outperforms the other benchmark recommendation techniques in terms of prediction accuracy and quality. Zhao et al. [35] introduced a hotel selection model based on a Probabilistic linguistic Term Set that incorporates ratings and reviews from several websites and accounts for the imbalanced influence of positive and negative evaluations. When compared to standard hotel selection models, the proposed recommendation model can provide consumers with more reliable and objective recommendations, according to a case study based on four hotels on the TripAdvisor, Ctrip, and Hostelworld websites.

As shown above, most of the studies only consider the ratings or reviews to produce personalized hotel recommendations. However, the use of only explicit rating information is not always convenient due to the sparsity problem that is inherent in the hotel recommendation domain [6, 33]. Besides, processing reviews is a demanding natural language processing activity for a variety of reasons. To begin with, reviews are often written by mere internet users; as a result, they are not always well-written and frequently include misspellings and typographical errors. Furthermore, due to the wide range of authors, there are variations in the vocabulary and grammar of the written reviews. Additionally, vague words and abbreviations are occasionally utilized. At last, reviews are usually brief, hence, they are usually subject to misinterpreting the entity being reviewed [19].

Accordingly, the strength of the proposed work in this study lies in 1) the adoption of multi-criteria ratings to enhance the prediction accuracy, and 2) the utilization of users' and items' implicit similarity, users' similarity propagation, and user/item reputation concepts to address the data sparseness challenge in this domain.

3. The Proposed Work

In this section, we explain the major components of the proposed FBMCCF model that integrates the enhanced user-based CF and an enhanced item-based CF approaches within an MC-based CF framework. The FBMCCF model adopts the similarity-based approach introduced by Adomavicius and Kwon [2]. It consists of three components: the enhanced user-based CF and the enhanced item-based CF, and the prediction fusion. The details of the three components are demonstrated in the following subsections.

3.1. The Enhanced User-based CF Component

The role of this component is to generate MC user-based predictions by utilizing users' similarities in the traveler-traveler implicit similarity matrix in addition to traveler's reputation. This component consists of four main building blocks:

1 User-based Direct Implicit Similarity

An enhanced metric for user-based similarity that considers distance information, structural similarity information, and extreme behavior information is proposed in order to enhance the user-based CF prediction performance.

Initially, the direct implicit similarity between any pair of travelers is calculated by using their ratings to compute the accuracy of the prediction of a given traveler as a trustworthy recommender to another traveler. For instance, based on their past ratings, travelers a and b have to obtain a high implicit similarity score if traveler b is able to deliver precise recommendations to traveler a. For this reason, the Resnick's prediction method [23] is utilized to generate the predicted rating of hotel x for a given traveler, a, based on only one neighborhood traveler, b.

$$P_{a,x} = \overline{r}_a + (U^b(x) - \overline{r}_b), \quad (1)$$

where $\overline{r}_a$ and $\overline{r}_b$ refer to the average overall ratings of the travelers a and b, respectively. $U^b(x)$ is the overall utility (i.e., overall rating) of traveler b respecting hotel x, and is expressed as an additive value function as follows:

$$U^b(x) = \sum_{d=1}^{h} w_d^b(x) \times c_d^b(x), \text{ where } \sum_{d=1}^{h} w_d^b(x) = 1, \quad (2)$$

where $w_d^b(x)$ is the importance weight of criterion c_d on hotel x by traveler b, and $c_d^b(x)$ is the rating of criterion c_d on hotel x by traveler b.

Then, a weighted version of the Euclidean distance method [2], in which it is combined with the Inverse User Frequency measure [8], is utilized to compute the initial implicit similarity of travelers a and b, based on the distance among the ratings and predicted ratings of the co-rated hotels, and the importance of the co-rated hotels in the similarity calculation.

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

where $I_{a,b}$ is the set of hotels that have commonly rated by travelers a and b. $P_{a,x}$ is the predicted rating of traveler a on hotel x. U *is* the total set of travelers in the rating matrix, and U_x is the set of travelers who rated hotel x.

To overcome the limitation of considering only the predictions error of co-rated hotels in the above metric, the Rating Jaccard method [7] is used as a structural similarity measurement to consider the ratio of total common ratings that are equal in absolute value to total common ratings. The more common hotels that have been equally rated amongst the two travelers, the higher the level of similarity between them.

$$URJacc_{a,b} = \frac{|N_{T(a,b)}|}{|I_a \cap I_b|}, \quad (4)$$

where N_T(a,b) is given as follows:

$$T(a,b) = \begin{cases} N_{T(a,b)} + 1; & \text{if } \forall_{x\in I_a \cap I_b} \ R_{a,x} = R_{b,x}, \\ N_{T(a,b)} \text{ remains unchanged}; & \text{otherwise} \end{cases} \quad (5)$$

where N_T(a,b) is the total number of common ratings that have the same absolute value. I_a and I_b are the sets of hotels rated by travelers a and b, respectively.

Furthermore, an extreme behavior similarity measure [13] has been applied as a weighted factor to deal with the sparsity issue. The extreme behavior similarity measure considers two types of extreme behavior between users: 1) Consistent extreme behavior, which suggests that users giving an extreme rating (such as 1 or 5) on the same item are further similar than users providing a neutral rating (such as 3); and 2) Individual extreme behavior, which suggests that a user's exceptional rating on an item is more significant than the public rating.

$$S1(a_x, b_x) = \frac{1}{1+\exp\left(-\left|U^a(x) - \overline{r}_{med}\right|\left|U^b(x) - \overline{r}_{med}\right|\right)}, \quad (6)$$

S1(a_x,b_x) corresponds to the contribution of the extreme overall ratings of travelers a and b on hotel x compared with the median rating $\overline{r}_{med}$ on the system.

$$S2(a_x, b_x) = \frac{1}{1+\exp\left(-\left|U^a(x) - \overline{r}_x\right|\left|U^b(x) - \overline{r}_x\right|\right)}, \quad (7)$$

S2(a_x,b_x) corresponds to the contribution of the extreme overall ratings of travelers a and b on hotel x compared with the mean overall rating of hotel x, $\overline{r}_x$.

$$UEBSim_{a,b} = \frac{\sum_{x\in I_{a,b}} S1(a_x, b_x) \times S2(a_x, b_x)}{\sqrt{\sum_{x\in I_{a,b}} S1^2(a_x, b_x)} \times \sqrt{\sum_{x\in I_{a,b}} S2^2(a_x, b_x)}}, \quad (8)$$

$UEBSim_{a,b}$ corresponds to the extreme behavior similarity measure between travelers a and b. Eventually, the enhanced implicit user-based similarity metric for any given pair of travelers is defined by:

$$iUSim_{a,b} = UeEucSim_{a,b} \times URJacc_{a,b} \times UEBSim_{a,b}. \quad (9)$$

2 User-based Similarity Propagation

An implicit similarity network is built as a directed graph once the direct implicit similarity is calculated. The nodes in this network represent travelers, while the edges show the degree of similarity between them. In view of the inadequate ratings that are frequently presented in most recommender systems, similarity propagation is required to spread the implicit similarity through the network. By doing this, new indirect connections are set among travelers who are not directly connected but are connected throughout intermediary travelers in the similarity network. For example, assume that travelers a and b have a direct connection and travelers b and c have a direct connection, by exploiting traveler b as an intermediary traveler, it can be inferred via similarity propagation that travelers a and c can have related preferences to a specific degree.

For that reason, the below aggregation metric is proposed to measure the propagated implicit similarity between travelers. For travelers a, b, and c, the propagated similarity that signifies to what degree traveler a is implicitly similar to traveler c via an intermediary traveler b, is figured as follows:

$$iUSim_{a,c}^{Prop} = \frac{\sum_{b \in intermediary\ (a\ and\ c)} \left(iUSim_{a,b} \times URJacc_{a,b}\right) + \left(iUSim_{b,c} \times URJacc_{b,c}\right)}{\sum_{b \in intermediary\ (a\ and\ c)} URJacc_{a,b} + URJacc_{b,c}}. \quad (10)$$

3 User Reputation

The traveler's reputation can be determined by the number of connections he has with other travelers in the implicit traveler-traveler similarity matrix, and the average variation between his ratings on hotels and hotels' average [31] as specified below:

$$UR_a = \exp\left(-\frac{\sum_{x \in I_a} \left| U^a(x) - \overline{r}_x \right|}{|I_a|} \right) \times \sqrt{\frac{|U_a|}{|U|}}, \quad (11)$$

where U_a is the set of travelers who are connected to traveler a.

4 User-based Predictor

For user-based predictions, the deviation-from-mean metric [15] is applied to produce user-based predicted ratings, as given below:

$$P_{a,x}^{U} = \begin{cases} \overline{r}_a + \dfrac{\sum_{b \in N^U} iUSim_{a,b} \times (U^b(x) - \overline{r}_b)}{\sum_{b \in N^U} iUSim_{a,b}}; \text{ if } iUSim_{a,b} \neq 0 \\ \overline{r}_a + \dfrac{\sum_{b \in N^U} UR_b \times (U^b(x) - \overline{r}_b)}{\sum UR_b} \quad ; \text{ if } iUSim_{a,b} = 0 \end{cases}, \quad (12)$$

where N^U is the set of Top-n nearest neighbors (travelers) to the active traveler a.

3.2. The MC Item-based CF Component

1 Item-based Implicit Similarity

An enhanced metric for item-based similarity that considers both distance information and structural similarity information is proposed in order to enhance the MC item-based CF prediction performance.

Primarily, the direct implicit similarity between any pair of hotels is calculated by using their ratings to compute the accuracy of the prediction of a given hotel as a trustworthy recommender to another hotel. For example, based on their past ratings, hotels x and y have to obtain a high implicit similarity score if hotel y is able to deliver precise recommendations to hotel x. For this reason, the Resnick's prediction method is again utilized to generate the predicted rating for traveler a of a given hotel, x, based on only one neighborhood hotel, y.

$$P_{a,x} = \overline{r}_x + (U^a(x) - \overline{r}_y), \quad (13)$$

where $\overline{r}_x$ and $\overline{r}_y$ refer to the average overall ratings of the hotels x and y, respectively. $U^a(x)$ is the overall utility (i.e., overall rating) of traveler a respecting hotel x.

Subsequently, a weighted version of the Manhattan similarity method [16], in which it is combined with the Inverse Item Frequency measure [8], is exploited to calculate the initial implicit similarity between hotels x and y, based on the distance among the ratings and predicted ratings of their co-rated travelers, and the importance of the co-rated travelers in the similarity calculation.

$$IeManSim_{x,y} = \frac{1}{1+\sum_{a\in U_{x,y}}\left|P_{a,x} - U^a(x)\right|} \times Log\left(\frac{|I|}{\left|I_{a\in U_{x,y}}\right|}\right)^2, \quad (14)$$

where $U_{x,y}$ is the set of travelers who have commonly rated hotels x and y. $P_{a,x}$ is the predicted rating of traveler a on hotel x. I is the total set of hotels in the rating matrix, and Ia is the set of hotels rated by traveler a.

To alleviate the drawback of considering only the predictions error of co-rated users in the above metric, the Salton's cosine index [32] is used as a structural similarity measurement to consider the proportion of total common travelers who have rated both hotels. The more common travelers who rated both hotels, the higher the extent of similarity among hotels.

$$SCI_{x,y} = \frac{\left|U_x \cap U_y\right|}{\sqrt{\left|U_x\right| \times \left|U_y\right|}}, \quad (15)$$

where U_x and U_y are the sets of travelers who rated hotels x and y, respectively Finally, the enhanced implicit item-based similarity metric for any pair of hotels is defined as:

$$iISim_{x,y} = IeManSim_{x,y} \times SCI_{x,y}. \quad (16)$$

2 Item Reputation

The hotel reputation is determined by the number of connections the hotel has with other hotels in the implicit hotel-hotel similarity matrix, and the average variation of its ratings as specified below:

$$IGR_x = \exp\left(-\frac{\sum_{a\in U_x}\left|U^a(x) - \bar{r}_a\right|}{\left|U_x\right|}\right) \times \sqrt{\frac{\left|I_x\right|}{|I|}}, \quad (17)$$

where I_x is the set of hotels that are connected to hotel x.

3 Item-based Predictor

For item-based predictions, the deviation-from-mean metric [15] is employed to produce item-based predicted ratings, as given below:

$$P^I_{a,x} = \begin{cases} \bar{r}_x + \dfrac{\sum_{y\in N^I} iISim_{x,y} \times (U^a(y) - \bar{r}_y)}{\sum_{y\in N^I} iISim_{x,y}} & ;\text{ if } iISim_{x,y} \neq 0 \\ \bar{r}_x + \dfrac{\sum_{y\in N^I} IR_y \times (U^a(y) - \bar{r}_y)}{\sum_{y\in N^I} IR_y} & ;\text{ if } iISim_{x,y} = 0 \end{cases}, \quad (18)$$

where N^I is the set of Top-n nearest neighbors (hotels) to the target hotel x.

3.3. The Prediction Fusion Component

As it has been shown that the best performance of rating prediction is achieved when several recommendation approaches are hybridized, the switching hybridization strategy [9] is used to switch between the recommendation approaches depending on a certain condition. The criterion for an approach selection is the recommender's capacity to generate a predicted rating. If both recommendation approaches are capable of generating a predicted rating, the harmonic mean metric [22] is used to merge the predicted scores.

$$P_{a,x} = \begin{cases} 0 & ; \quad \text{if } P^U_{a,x} = 0 \text{ and } P^I_{a,x} = 0 \\ P^U_{a,x} & ; \quad \text{if } P^U_{a,x} \neq 0 \text{ and } P^I_{a,x} = 0 \\ P^I_{a,x} & ; \quad \text{if } P^U_{a,x} = 0 \text{ and } P^I_{a,x} \neq 0 \\ \dfrac{2\times P^U_{a,x} \times P^I_{a,x}}{P^U_{a,x} + P^I_{a,x}} & ; \quad \text{if } P^U_{a,x} \neq 0 \text{ and } P^I_{a,x} \neq 0 \end{cases}. \quad (19)$$

4. Experiments

Several experiments were carried out using a real-world MC dataset and evaluation measures to assess the performance of the proposed FBMCCF model in comparison with other recommendation methods.

4.1. Dataset

To evaluate the proposed model, the TripAdvisor MC dataset [17] is used for the experimental validation. The dataset includes 28,829 multi-criteria ratings of 1039 users on 693 hotels. The rating scale of users ranges from 1 to 5 on seven criteria: cleanliness of the hotel, value for money, location of the hotel, quality of rooms, overall quality of services, quality of check-in, and particular business services. The level of the sparsity of the TripAdvisor dataset is 96%. The dataset was divided into two parts: the training set (80%), and the test set (the remaining 20%).

4.2. Evaluation Measures

Two well-known metrics, *Mean Absolute Error* (MAE) and *Root Mean Square Error* (RMSE), are utilized to measure the predictive accuracy of the proposed and benchmark recommendation methods. Both metrics measure how much predicted rating is close to the actual rating. The lower values of MAE and RMSE, the higher the achieved predictive accuracy is. 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 [4].

4.3. Comparison Methods

To compare and verify the performance of the proposed model, three CF-based benchmark algorithms have been chosen, including two conventional multi-criteria CF algorithms: the Multi-Criteria User-based CF (MC-UBCF) and the Multi-Criteria Item-based CF (MC-UBCF) [2], in addition to a recent multi-criteria recommendation algorithm: the Multi-Criteria User-based Trust-enhanced CF (MC-TeCF) [24].

4.4. Experimental Results

A set of experiments were designed and conducted to verify the effectiveness of the proposed model against the benchmark algorithms. In experiments, comparison results of the predictive accuracy between the proposed model and three benchmark CF algorithms on three real-world MC datasets are presented. Besides, comparison results of the predictive accuracy and coverage between the proposed model and three benchmark CF algorithms under varying levels of sparsity are also demonstrated.

4.4.1. Comparison Results on TripAdvisor Dataset

Experiments were carried out on the TripAdvisor dataset to compare the predictive accuracy results of the proposed FBMCCF model with other benchmark algorithms by changing the maximum number of nearest neighbors involved in the prediction process. The predictive accuracy is measured using MAE and RMSE.

Figure 2 and Figure 3 compare the MAE and RMSE values obtained by the proposed FBMCCF model and other benchmark algorithms at different numbers of nearest neighbors. The proposed model significantly outperformed the other algorithms in terms of MAE and RMSE at all numbers of nearest neighbors. The average MAE value of the proposed model is improved by approximately 38%, 27%, and 10%, respectively, compared with the average values obtained by other benchmark algorithms. The average RMSE value of the proposed model is improved by approximately 40%, 28%, and 4%, respectively, compared with the average values obtained by other benchmark algorithms.

Figure 2
Comparison results of MAE on TripAdvisor dataset

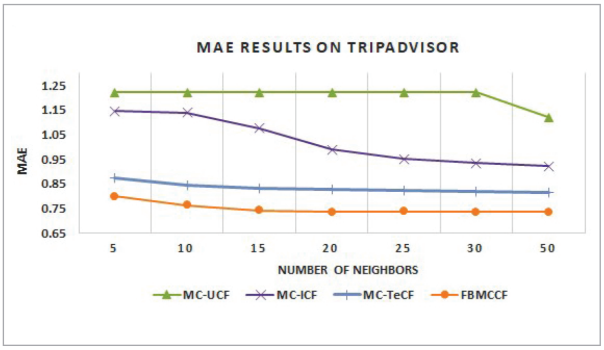
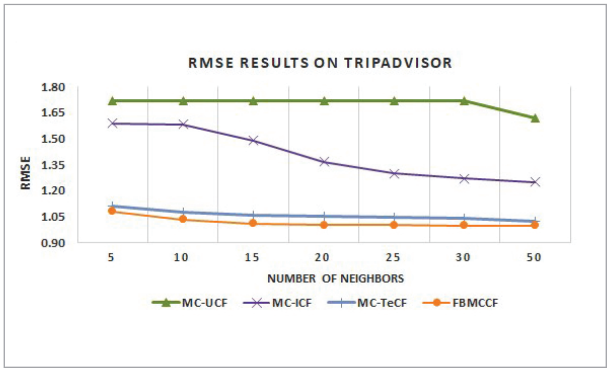


Figure 3
Comparison results of RMSE on TripAdvisor dataset



As demonstrated by the figures, the proposed FBMCCF model attains the best predictive performance results compared with other algorithms, whether in MAE or RMSE, because it not only considers the multi-criteria ratings that precisely express travelers' complex preferences, but also takes the implicit information about relationships among users and relationships among items into account.

4.4.2 Comparison Results on Various Sparse Datasets

To deal with the sparsity problem, the FBMCCF model exploits implicit information about users' and items' relationships to extend the user's and item's neighborhood to improve the recommendation performance. This implicit information is extracted based on the available ratings using the proposed users' and items' implicit similarity, users' similarity propagation, and user/item reputation techniques.

Figure 4 and Figure 5 depict the MAE and Coverage obtained by the proposed FBMCCF model and other benchmark algorithms using six sparse datasets, which were created by randomly removing ratings to retain 99.8%, 99.5%, 99%, 98.8%, 98.5%, and 98% sparsity levels. It can be seen that the MAE increases as the sparsity increases, while the Coverage increases as the sparsity decreases. This is to be expected, as increasing sparsity results in a poor set of nearest neighbors, thus reducing prediction accuracy and coverage. In all cases, the results show that the proposed FBMCCF model, due to the extended set of nearest neighbors for users and items, achieves lower MAE values and higher Coverage percentages than the compared benchmark algorithms at each sparsity level.

Figure 4

Comparison results of MAE for different levels of sparsity

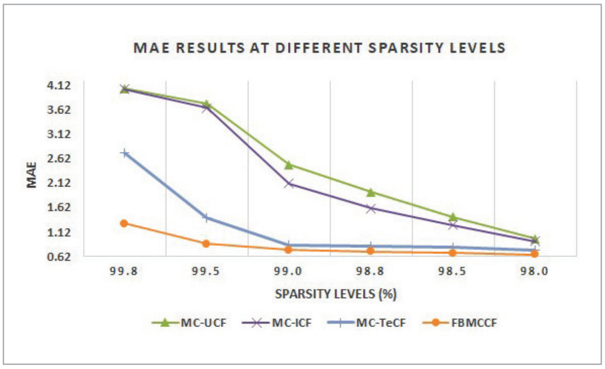
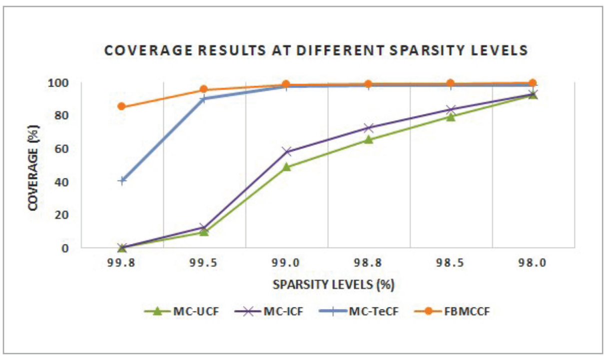


Figure 5

Comparison results of Coverage for different levels of sparsity



The results show that compared with the benchmark algorithms, the MAE of the proposed model is improved by approximately 66%, 63%, and 32%, respectively. Whereas the Coverage is improved by approximately 49%, 45% and 10%, respectively. In the case of extreme sparsity, in the 99.8 % sparse dataset, the FBMCCF model improves predictive accuracy by 68%, 68%, and 52% over the benchmark methods, respectively. Furthermore, in the 99.8% sparse dataset, the benchmark conventional MC CF algorithms were unable to produce any recommendations in the test set, and the benchmark MC user-based trust-enhanced CF recommendation approach is only able to make recommendations for 40% of the available items in the test set, whereas the FBMCCF model can make recommendations for up to 85% of the available items in the test set.

Accordingly, the significant improvement in MAE and Coverage results shows that the proposed model is a more robust choice than other benchmark algorithms to deal with extremely sparse datasets.

5. Conclusion and Future Work

Traveling has become a popular recreational and stress-relieving activity for a variety of reasons, including learning about new cultures, exploring new places, and experiencing adventures. The development of hotel booking services such as Tripadvisor.com, Agoda.com, and Expedia.com has made it easier for ordinary people to access tourist places without a great deal of reliance or effort. Current hotel websites, on the other hand, are not very interactive with travelers, leaving them as platforms that solely contain hotel information, with ratings and reviews to aid decision-making. Going through a plethora of ratings and reviews is a tedious task for most travelers, making decision-making even more difficult. As a result, novel recommendation systems that can utilize the available information to deliver personalized hotel recommendations to travelers need to be developed.

Thus, for this reason, this paper proposes an effective hotel multi-criteria recommendation model to help travelers select hotels that match their preferences. The proposed model is a fusion of an enhanced user-based CF and an enhanced item-based CF approaches within the MC-based CF framework. The proposed model: 1) enhances the prediction accuracy of hotel recommendations by the deployment of multi-criteria ratings that precisely express travelers' complex preferences; and 2) exploits the users' and items' implicit similarity, users' similarity propagation, and user/item reputation concepts to address the sparsity challenge that is caused by the insufficiency of rating information in the hotel domain, with no need for external information from other information sources.

The proposed model was built and evaluated on the TripAdvisor dataset, which is a real-world hotel MC dataset. Mean absolute error and root mean square error were used to assess predictive accuracy, and coverage was used to assess prediction coverage. Three CF-based benchmark algorithms were used to verify the performance of the proposed model. On the TripAdvisor dataset, the model performed better than other benchmark algorithms in terms of predictive accuracy, with an average improvement of 16%. In sparse datasets, the model outperforms other benchmark algorithms by average improvements of 44% in predictive accuracy and 27% in prediction coverage. In the future, it will be an interesting direction to further enhance the performance of the proposed model by incorporating other contextual information related to hotels, such as location, season, and weather into the recommendation process.

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