A Novel Model for Explainable Hostel Recommender System Using Hybrid Filtering

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ABSTRACT

Recommender systems help humans in filtering and finding the right information from the enormous amount of data. Hostels are more famous than hotels for solo travelers, but no prior research related to recommender systems has been conducted in this domain. Hostels allow users to provide multi-criteria ratings and traditional recommender systems are not able to provide effective recommendations in case of multi-dimensionality i.e. contextual information and multi-criteria ratings. So, we have proposed a novel hybrid recommender system (SAFCHERS) that chooses the hostel's features for computation dynamically and provides explainable and better recommendations than the traditional recommender systems.

KEYWORDS: Hybrid Recommender System, Multi-Criteria Ratings, Dynamic Feature Selection, Explainable Hostel Recommendations, Switching and Feature Combination.

1. INTRODUCTION

Tourism is a trillion dollars industry [1] and solo traveling is very common [2]. Most of the solo travelers and backpackers prefer to stay in hostels [3] instead of hotels due to many benefits, some of which are mentioned below.

It is a reality that traveling is expensive. Accommodation, flights, food, and tourism activities all add up the expenses. So, most solo travelers tend to cut down unnecessary expenses like booking hotels for spending nights. Hostels in comparison to the hotels are cheaper [3], so the hostel is the first choice for backpackers.

For most solo travelers, socialize is the primary reason for choosing hostels over hotels because no one wants to get bored while traveling. Hostels have a social ambiance [3] and when you are sharing a room with other solo travelers, it becomes quite easy to make friends and enjoy the tourism activities with a friend or group of other solo travelers.

Unlike hotels where you have to spend a good amount of money on your food too, most

hostels have a kitchen [3] where you can cook your own food to save money and enjoy your own cooked food.

Most of the hostels offer fun activities [4] to the travelers to take care of their entertainment, for example, they can offer an activity like hiking in groups, etc.

The front desk gives insights to the backpackers of famous places or activities to do in that city by providing them maps and brochures. Moreover, you meet other travelers in hostels who will tell you about their experiences with various activities that give you enough free information to make your mind [5].

Recommender systems help humans in making the decision by giving them personalized information. The recommender system normally gathers the user's data, finds patterns in user behavior, extracts valuable insights, calculates probabilities, compares them with the available item inventory and then

presents the most plausible matches. Today, recommender systems have become very important in our life and are being used for different purposes like for recommending movies [6], music [7], [8], books [9], news [10], or ecommerce [11] products.

2. BACKGROUND AND RELATED WORKS

Ferrari Dacrema et al. have highlighted some important issues related to current recommender system research practices in this paper [12]. Deep learning is not necessarily the optimal solution for every problem, however, most of the researchers today tend to use deep learning in current recommender systems without the consideration that if that problem can be solved better by using simpler machine learning algorithms. The approach used in paper [12] is quite unique where most researchers today are experimenting on developing more complex deep learning algorithms, Ferrari [12] experimented to reproduce the 18 neural algorithms that were presented at recent top-level research conferences to keep track of what represents the state-of-the-art at the moment.

However, results were shocking as only 7 out of 18 could be reproduced with quite an effort and among which 6 were outperformed at least on some datasets with simpler methods like the nearest neighbor. Although, the remaining algorithm (Mult-VAE) outperformed the baselines even that could not outperform a well-tuned non- neural linear ranking method. The findings presented in the paper raise many questions on the quality of scientific research being conducted in this domain and suggest improving scientific practices in this area.

Afoudi et al. [13] chose the content-based recommender system approach over the traditional collaborative filtering (CF) approach for the restaurant recommendation system because the traditional CF recommender system does not show satisfying performance when having contextual data and data sparsity. The experiment results in this paper suggest that choosing the right features for computing similarity has a high impact on the performance of the content-based recommender system so different techniques to select features are also discussed in this paper. Also, the Euclidean distance algorithm gave better results than the

classical cosine similarity method in this research experiment.

Chen et al conducted research [14] to find out which quality factors of hostels are aligned with the customer's satisfaction and loyalty. For this research work, only five quality attributes were considered, and results show that three out of five play an important role in customer satisfaction. That is why the hostel has a multi-dimensional or multi-criteria rating and those attributes are important for the customers while choosing a hostel. So here a recommender system cannot work properly only on a single overall rating. All the rating attributes which sum the overall rating needs to be computed separately so that the recommender system can provide effective and more personalized recommendations.

Mohammed Al-ghuribi et al also has highlighted the importance of multi-criteria rating recommender systems in this paper-[15]. By utilizing only, a single overall rating, a recommender system cannot give promising results where the data is available in multiple criteria rating. Different recommender system techniques are discussed in this paper to tackle multi rating reviews data. The paper also suggests that combining a content-based recommender system and collaborative filtering recommender system into a hybrid recommender system can solve the important issues of both techniques like sparsity, cold start, and scalability.

Zhang et al have explained in this paper, [16] how explainable recommendations can help to improve effectiveness, transparency, satisfaction, and persuasiveness of recommender systems. The lack of explainability can be less effective and less persuasive for the users to accept the results which can decrease the system's trustworthiness. In some areas for example medical field, explainable recommendations become almost necessary for medical workers to make medical diagnoses. The explainable recommendation gives reason to the user why to trust a recommendation. The explanation may come from the model itself or can be post-hoc. Recently a lot of research is being conducted in this area and being applied in real-world systems. For example,[17] has proposed a novel explainable model UniWalk that explains why items are recommended together.

3. TYPES OF RECOMMENDED SYSTEM

Mostly recommender systems are classified into the following eight types.

3.1. Popularity Based Recommender System

As the name suggests, these recommender systems recommend trending items or products to the user. For example, if a piece of news is getting viral then that news will be recommended to the new user. This type of recommender system has its own benefits and drawbacks. The benefits can be considered as novelty, diversity, and serendipity [18] because the recommendation provided by these recommender systems is not personalized [19] but on the basis of trending items. However, even though the system knows the user behavior but provided recommendation is not personalized can be considered as a drawback. That is why this technique is used in a combination with other recommender system techniques like collaborative filtering recommender system.

3.2. Content-Based Recommender System

Content-based (CB) recommender system does not use the user's rating data but use item or product's attributes or metadata as the basis of recommendation. In the case of a book example, if poetry book is as a seed then the system will suggest similar poetry books to the user on the basis of matching metadata like the category of the books [9]. These recommender systems are ideal for the cold start problem since they do not rely on the user's rating data.

3.3. Collaborative Filtering Recommended System

Collaborative filtering (CF) recommender systems are quite different in working in comparison to content-based recommender systems as shown on Figure1. Unlike CB recommender systems, CF recommender systems need user's rating data to provide recommendations.

The user's feedback is very important in these recommender systems. Without the users' implicit or explicit rating data [20], CF recommender systems won't work effectively. These recommender systems are the most common type of recommender systems and are being used in a variety of famous applications like for product recommendation in Amazon.

There are two types of CF

recommender systems i.e., item-based, and user-based as shown on Figure2.

In item-based CF recommender systems, similar items are identified on the basis of the user's rating data. However, in user based.

Figure 1: Comparison between collaborative filtering and content-based filtering

CF recommender systems, similar users are identified who have a similar taste. For example, In the case of a movie.

Figure 2: Comparison between user-based filtering and item-based filtering

recommendation, the system matches the user's rating on movies with the other users' rating data on those movies and then recommends the new movie to the user which the other similar user has watched.

3.4. Hybrid Recommender System

When two different types of recommender systems like content-based recommender system and collaborative filtering recommender system are used in a combination then such a hybrid combination is called a hybrid recommender system as shown on Figure3.

This combination as a collective is considered a good recommender system as it solves the problems of both content-based recommender systems and collaborative

filtering recommender systems when used alone because both systems have their strengths and weaknesses. So, the hybrid recommender system combines the strengths of both recommender systems, cancels the weaknesses of both, and thus provides better and effective recommendations. The most common hybridization techniques are as follows.

Weighted: It combines the scores or weights of the two different recommenders [21] using weightage linear functions to generate the recommendation list. This is the most common hybrid technique.

Figure 3: Example of hybrid recommender system

Switching: This technique allows the system to use either recommender according to the situation. For example, use collaborative filtering where there is enough rating data otherwise use the content-based filtering approach [21].

Mixed: In this technique, the recommendation from each recommender is provided instead of one recommendation per item [21].

Feature Combination: Features of each different recommender is given as an input to a single recommendation algorithm to provide recommendation in this technique [21].

Feature Augmentation: In this hybrid technique, a feature or set of features is computed from one technique and then that becomes the input to the next technique [21].

Cascade: It is an iterative hybrid technique, the recommendation from one technique is then refined by the other technique [21].

Meta-level: The model created by one of the combined techniques becomes the input for the other technique [21].

3.5. Demographic Based Recommender System

These are among the simple type of recommender systems which take user's demographic data like age, location, gender, etc. and then give recommendations according to the classification of demographic data [22]. In the case of tourism activities, users are classified into different categories according to their location, age and gender data and then those users are provided the recommendations of tourism activities [23] according to their classes.

3.6. Utility-Based Recommender System

Utility-based recommender systems give recommendations by computing the usefulness or utility value of each product [24] for the user. The main advantage of using this type of recommender system is that the non-product attributes which are important in some scenarios such as vendor reliability and product availability are also used in the computation. Thus, this type of recommender system makes it possible to check the real-time inventory of the product and displays it to the user which is important especially in the case of ecommerce recommendations.

3.7. Knowledge-Based Recommender System

This type of recommender system is also called constraint-based recommender systems [25] because in these recommender systems user's preference is explicitly gathered first. Then these recommender systems use knowledge about products and users to make recommendations. A search web page with multi-filter controls to find products like cars or houses can be used as an example of a knowledge-based recommender system.

3.8. Context-Aware Recommender System

In normal life, social, cultural, economic, and psychological contexts of a user influence the user's decisions. This type of recommender system handles such situations effectively. For example, in the news domain, the user can have different short-term and long-term preferences. In such scenarios, a context-aware recommender system like session-based recommenders [10] can fulfill user's short-term

preferences or temporal dynamics. A lot of progress has been made [18] and still more research is being conducted in this type of recommender system.

Each type of these recommender systems has its advantages and disadvantages that is why these recommender systems are mostly used in combination to solve the famous challenges in recommender systems.

4. CHALLENGES IN RECOMMENDER SYSTEMS

These are the famous challenges in the domain of recommender systems.

4.1. Cold Start Problem

This problem arises when a new user or product is added to the existing system or when an entirely new website is started. In this scenario, because there is no historical rating data for both the new product or user, it is difficult for the CF recommender system to give accurate recommendations [22], [26].

4.2. Sparsity

This is considered a severe kind of problem in CF recommender systems where the user has a large matrix of data like watched movies [6] but the user has not given the rating for those movies. So, the sparse rating makes it difficult for the CF recommender system to provide accurate recommendations.

4.3. Scalability

The scalability refers to the problem that the performance of the recommender system does not degrade even though the new users and items are getting increased in the system [27].

4.4. Latency Problem

Since CF recommender system recommends on the basis of ratings of the user. The new items, however, are not recommended in this type of recommender systems until those newly added items get ratings from the users. This causes the latency problem [28].

4.5. Serendipity

To increase the performance, the recommender systems are expected to sometimes recommend some unexpected items to the user which the user was not expecting. This gives the user some diversification [18] which is important because too much

personalization or overspecialization is also not considered good in recommender systems.

4.6. Limited Content Analysis

Content-based recommender systems [9], [29] rely on the content of the item. If there is not enough information regarding the item's attributes, then it becomes difficult for the CB recommender systems to give accurate recommendations.

4.7. Privacy

The more the data, the better the recommendation will be provided by the recommender systems, but this can result in issues like a compromise on data security and privacy. Cryptographic mechanisms and randomized perturbation techniques [30] can be used to solve this problem.

4.8. Shilling Attacks

This problem occurs when some competitor or malicious user starts spamming by giving a false rating to one or more products to increase or decrease the item's popularity. This problem can result in reduced performance or less accurate recommendations [31]

4.9. Gray Sheep

This problem happens when the opinions of the user do not match with any group and the user is unable to get the recommendation due to no match with any other user. Such users can be identified and separated from others by using offline clustering techniques like k-mean clustering so that the recommendation error gets minimal [32] and the performance can be increased.

4.10. Synonymy

This problem occurs when an item is represented with two or more similar names. In such a scenario it becomes difficult for the system to identify whether the terms represent the same item or different items. For example terms like “comedy movie” and “comedy film” can be treated differently in common recommender systems [33]. Considering the importance of tourism [34] and recommender systems, a lot of research has been conducted in the area of tourism. There are many recommender systems to recommend hotels [35], restaurants [13], flights [36] and tourism [23] activities but no research related to recommender systems has been conducted in the domain of hostels.

A good hostel recommender system not only will help the web- site to increase the sales [37] but it will facilitate the users to choose the right hostel according to their needs among a lot of hostels with minimum efforts. The right hostel recommendation at the right time will give the users the best experience and it will help to win customers' trust and loyalty which will give them the reason to come back to the website for further bookings [5].

5. PROPOSED APPROACH

The primary goal of this research project is to recommend such hostels to the users which they are most likely to book. So, when a user clicks on a specific hostel and lands on the detailed page (called as an anchor hostel), It is obvious that the user is interested in that kind of hostel. So, the idea is to facilitate the user by showing similar hostels on the detailed page. This way, the user can select the best hostel among the inventory according to the specific needs.

5.1. Switching and Feature Combination Hybrid Explainable Recommender System (SAFCHERS)

Since there is abundant contextual and multi-rating hostel data, so a hybrid recommender system by combining the content-based and item-based collaborative filtering approach is the ideal solution here. Such a hybrid combination [19] is being used in different applications commonly but for this project, a unique hybrid technique is proposed which is the combination of switching [38] and feature combination [39] technique.

This combination combines the strengths of both approaches, cancels the weaknesses of both approaches [21] and is ideal to solve famous recommender system problems like cold start, latency and sparsity. For example, when the new hostel is added and there is no rating data then the system will switch to the content-based approach to find similar hostels. When there is no contextual information and the hostel has only rating data then by using the switching approach, the system will use item-based collaborative filtering to recommend similar hostels. Also, when both rating and contextual data is available, the system will combine the features like rating attributes and other contextual attributes in a single algorithm to compute the similarity in order to provide

effective recommendations.

Most of the recommender systems today give recommendations but they do not give an explanation [16] to the user that why the specific recommendation has been provided. The main reason is that the complex algorithms are being used in these systems and those are difficult to explain. Due to the lack of transparency in such recommendations, most of the users lack trust in such recommendations and as a result, such recommendations become less effective and less persuasive.

Here the system will provide an explanation [17] for the provided hostels' recommendation to increase the performance overall. The basic algorithm for explaining the recommendation is as follows.

```

while All features do
  if Rating feature is rated 8 or more than 8 then
    Take this rating feature for explanation
  end if
  if Contextual feature is present in the hostel then
    Take this contextual feature for explanation
  end if
end while

```

So, the system mentions those rating attribute in the explanation that have 8 or more than 8 rating common in all the recommended hostels. Also, the system picks those hostel contextual attributes for the explanation that are common in all the recommended hostels.

5.2. Dynamic Feature Selection

In content-based recommender systems or hybrid recommender systems [21] where the content-based recommender system is being used in a combination with any other recommender system approach, feature selection [13] becomes very important, especially with the contextual data. In this research experiment, the hostel's features which are aligned with the customer's satisfaction [14] are selected initially. Then the algorithm is trained so that it selects the features among the initially selected features for similarity computation dynamically and intelligently, unlike the other algorithms. The basic algorithm for dynamic feature selection is as follows.

```

while All features do
  if Rating feature is rated then
    Take this rating feature for similarity

```

computation

end if

if Contextual feature is present in the hostel **then**

Take this contextual feature for similarity computation

end if

end while

For example, if there is no Wi-Fi available in the anchor hostel, the algorithm will not take Wi-Fi feature in similarity computation so that the recommended hostels can have those hostels that have Wi-Fi too. Otherwise, an algorithm with static features [34] would only recommend those hostels that do not have Wi-Fi.

5.3. Euclidean Distance

The similarity between two vectors can be computed by using Euclidean Distance [13]. Here the distance is basically the similarity between vectors. So, if there is less distance

between two vectors, it means those vectors are quite similar and if there is more distance, it means the similarity between the vectors is less. The Euclidean distance between hostels p and q is defined as follows.

$$d(p, q) = ((p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2)^{1/2} \quad (1)$$

5.4. Evaluation

It is important to identify the key factors for evaluating the quality of the recommendations. Offline evaluation metrics like Euclidean distance [4], RMSE [40] and MAE [40] will be used in this experiment to evaluate the recommendations. RMSE and MAE are statistical accuracy metrics that evaluate the accuracy of the recommendations and can be computed by using equation 2.

$$MAE = \frac{1}{N} \sum |predicted - actual| \quad | \quad RMSE = \sqrt{\frac{1}{N} \sum (predicted - actual)^2} \quad (2)$$

Overall, the crux of this research is to infer as much as a realistic picture of the situation, the intent of the user and exploiting the best possible information in the hostel recommender system to satisfy users' expectations [14]. By providing nearly all the possible decision variables to the recommendation engine, it is likely to mimic human behavior in choosing the hostels.

6. EXPERIMENTS AND RESULTS

6.1. The dataset

Since there is no public data-set available related to hostels on the internet so for this research work, the data is scraped from the famous Hostel World website[41]. The scrapped hostels data has all the important information about hostels available on the website except the individual users' reviews data. There are two types of columns in the data-set i.e. multi-criteria rating –[15] attributes (value for money, security, location, staff, atmosphere, cleanliness, and facilities) and hostel properties attributes (board games, DVD, foosball, games room, play station, pool table, Wi-Fi, distance, city, and price). The distance in the hostel properties attributes is the distance from the city center. The rating attributes has the average rating of all the users who have rated that hostel.

6.2. SAFCHERS Experiment Steps

The first step is to cleanse the data by dropping those features [13] which are not necessary for similarity computation to increase the performance of the algorithm. So, the features summary, score, name, and rating. Band is dropped. The name of the hostel can be accessed later once the computation is done so this feature is dropped. Summary. The score gives the overall rating of the hostel and rating. Band column classifies the overall rating. Both these columns are not necessary for similarity computation because, in this experiment, the emphasis is on matching the specific rating attributes like security, etc rather than overall rating so that users can get personalized [19] hostel recommendations.

The missing values are handled and then the feature space [42] is normalized by converting each column or feature into a standard score. The choice of the normalization scheme normally depends on the data and the problem because here the data is normally distributed so a standard score approach is used here. The most important thing in the hostel recommendation is that the system shows only those hostels as recommendations that are within the city of the anchor hostel, so the model is designed to handle this constraint.

The model first checks the value of the columns of the anchor hostel to select the features for computation. Those features are not selected which has 0 value and the algorithm picks all those features which have other than 0

value. The 0 value in a column means that the hostel either does not have that feature or is not rated yet for that feature. Then the Euclidean distance is computed between the anchor hostel and the other pieces of inventory to recommend similar hostels. The recommended hostels are then sorted in such a way that those hostels come on the top which has the least distance means are similar to the anchor hostel. Finally, the model provides an explanation for the provided hostels' recommendations.

6.3. SAFCHERS Experiment Results

Since the goal of this research project is that the system provides effective hostel recommendations in both scenarios i.e when there is rating data and when there is no rating data. So, it is mandatory to test the SAFCHERS that how it performs in both scenarios. The first case is when the anchor hostel's most columns have some value other than 0. For example, for hostel id 8, only 3 columns i.e board games, DVDs and PlayStation have 0 value and the rest 14 columns have a value other than 0. Table 1 shows the result of the SAFCHERS experiment for hostel id 8.

Table 1. SAFCHERS result for hostel id 8

ID	Atmosphere	B.Games	PlayStation	Similarity
8	8.2	0	0	0.000000
10	8.2	1	0	0.604560
2	8.2	1	1	0.766643
14	8.1	1	0	3.597192

The result is satisfactory as the recommended hostels are from the same city and are closely matching the anchor hostel in all the attributes. Due to feature combination, the recommended hostels are not only similar in rating but are also similar in other important hostel properties like Wi-Fi. As per the rules, the model did not take the features of board games, DVDs and play station for similarity computation. That is why the recommended hostels have the board games option in them and even one of the recommended hostels has play station facility in it. Also, the system is explaining the recommended hostels. Here

because the atmosphere rating is 8 or above 8 in all three recommended hostels so it is mentioned in the explanation. Also, the board games are available in all three recommended hostels, so it is also mentioned in the explanation.

Let's analyze the results of hostel id 8 returned from the traditional model [43] which takes all the features for similarity computation.

Table 2. Traditional model result for hostel id 8

ID	Atmosphere	DVD's	PlayStation	Similarity
8	8.2	0	0	0.000000
10	8.2	0	0	2.144130
14	8.1	0	0	4.143862
13	7.4	0	0	4.430284

As shown in Table 2, the traditional model [43] has returned only those hostels which do not have DVDs and play station facility because the anchor hostel does not have these facilities. Such recommendations cannot be considered as good recommendations because the traditional model is ruling out all those hostels that have DVDs and play station facilities.

Let's compare the results using the Euclidean distance [4] between the traditional model which takes all features and SAFCHERS. Figure 5 is showing that clearly SAFCHERS is giving better hostel recommendations as each hostel recommendation from SAFCHERS is closer to the anchor hostel than the traditional model. Let's take the mean [44] of the Euclidean similarity of the provided recommendations from both models and compare them. As shown in Figure 6, clearly SAFCHERS is giving better recommendations.

When the new hostel is added to the system and has no rating, SAFCHERS is expected to provide effective hostel recommendations in this scenario too which is known as a cold start problem. For example, the hostel id 47 has 0 value for 14 columns out of 17. Here the switching technique with dynamic feature selection works so that it only selects three features i.e distance, city, and price for Euclidean distance computation. The SAFCHERS experiment results for hostel id 47 are shown in table 3.

Again, the result is satisfactory as all

Figure 4: Euclidean distance comparison for hostel id 8

Figure 5: Euclidean distance mean comparison for hostel id 8

Table 3. SAFCHERS result for hostel id 47 Similar hostels who are famous for excellent location

ID	Location	Wi-Fi	Distance	Price	Similarity
47	0.0	0	3	30.56	0.000000
33	8.7	1	3	34.00	0.129788
26	10.0	0	2	27.00	0.164429
39	8.0	0	4	26.34	0.185328

the hostels are from the same city, have a similar distance from the city center and have almost the same price. The model is explaining the recommended hostels and also, the recommendation includes those hostels which are rated by the users and one of the hostels has Wi-Fi too.

Table 4 shows the result of the traditional model [43] which clearly shows that the traditional model is only recommending those hostels which are new, not rated yet and do not have important properties like Wi-Fi, etc.

Clearly, SAFCHERS is giving better results for the newly added hostel too. So, in both scenarios, SAFCHERS has provided

explainable, personalized, and better recommendations than the traditional recommender system.

Let's evaluate the accuracy of the recommendations provided by both the traditional model and SAFCHERS by using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Table 5 shows the result of RMSE and MAE for both SAFCHERS and the traditional model. The lower value means more accurate predictions.

The result in table 5 shows that recommendations provided by SAFCHERS are more accurate than the recommendations provided by the traditional model because both RMSE and MAE values from the SAFCHERS column are lower than the traditional model.

Now we will explain the SAFCHERS learning process. Figures 8 and 9 show the learning process of SAFCHERS on the hostels' dataset. The accuracy changes during each iteration and the system perform learning with each iteration. It is quite clear that after only

Table 4. Traditional model result for hostel id 47

ID	Location	Wi-Fi	Distance	Price	Similarity
47	0.0	0	3	30.56	0.000000
32	0.0	0	3	43.52	0.488970
34	0.0	0	16	44.50	1.340514
44	0.0	0	15	17.85	2.399419

Figure 6: Euclidean distance comparison for hostel id 47

Table 5. Accuracy Metrics Comparison

Evaluation Metrics	SAFCHERS	Traditional Model
RMSE	0.783	0.924
MAE	0.598	0.727

Figure 7: Euclidean distance mean comparison for hostel id 47

Figure 8: SAFCHERS RMSE

Figure 9: SAFCHERS MAE

three iterations, the minimum test error is achieved.

7. CONCLUSION

Recommender systems help humans in filtering a large amount of data in today's era of big data. Recommender systems are very popular in the tourism domain and are being used effectively like for restaurant recommendations etc. but to date, no prior research related to recommender systems has been conducted for hostels. In this research project, a novel hybrid recommender system SAFCH-ERS is proposed and experimented on the hostels' dataset which has given better results than the traditional recommender system in both scenarios i.e. when the hostel is rated by many users and when the new hostel is added to the system and has no rating yet. SAFCH-ERS has

not only provided more accurate recommendations but also has provided the explanation for those recommendations which makes these recommendations more effective and more persuasive.

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