Location-Based Hotel Recommendation System

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Abstract. In recent years, the hotel industry in Taiwan has begun to flourish as the economy has grown. In order to attract more tourists to make changes in various services and facilities, the hotel's types have begun to make a difference. However, the content of the website is full of personal subjective or unilateral information, which is easy for tourists to lose in it or waste a lot of time cost. Therefore, we hope to provide more comprehensive hotel recommendations and use the traditional recommendation technology combined with location-based services to make recommendations. Different from the conventional recommendation, only comprehensive factors are considered. The study included three individual factors – service, price, facility to do a single rating and combined with the location of the tourist to make recommendations so that the recommendations can be closer to the needs of tourists. We selected 50 high-profile hotels, including five categories of mountain, sea, hot springs, theme parks, and resort hotels. Through the recommendation system, we recommend hotels that have not yet been lived by tourists, as a list of hotels to choose from it.

Keywords: Location-based services · Recommendation system

1 Introduction

With the carry out of the Taiwan government on the two days weekend, the domestic tourism trend has been gradually improved, and the hotel industry has been promoted. The choice of tourists in the hotel has been upgraded from the previous money-oriented to functional orientation, and the hotel has also improved from merely providing accommodation services to meeting the needs of tourists. Therefore, the hotel market began to divide into different tourist groups, and the hotel started to split into different design styles, plans, functions and so on. Besides, tourists themselves have different preferences for hotel choices. We believe that tourists will also affect the selection of the hotel because of their traits, personality, behavior and other factors. So how to provide tourists with a hotel that suits their preferences or needs is even more critical.

O'Mahony and Smyth [1] explored the hotel recommendation system and used TripAdvisor, an internationally renowned hotel recommendation website, as an example. The website can be selected based on the areas, prices, tourist's ratings,

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equipment, brands, etc. or advanced selected, such as value, romantic, family, luxury, business, etc. We understand that the collaborative filtering system develops the operation mode of the website. The photos taken by a large number of tourists are used to improve the authenticity of the website, and the tourist's ratings and comments are provided to make hotel reviews and convert to a built-in score to rank. In order to provide more accurate information, it is necessary to widely classify various types of hotels, and offer more types of hotels to provide consumers with choices, such as providing services for childcare and babies, services for hot spring hotels, and the hotels close to the ocean which can provide services for offshore facilities, these are passengers who can attract special needs.

With the rapid development of the Internet and information technology, it continues to influence and change the way of competition. The tourism industry is far-reaching influence by e-commerce. With the increasing demand for tourism by domestic tourists, the information provided by the current tourism website is mainly based on the suit travel itinerary. The travel websites have begun to provide simple screening to query travel itineraries, allowing users to enter destinations, countries, dates, hotels, etc., but the recommendation results are limited to fixed models. It will not produce different results for different types of people. The result of low interactions makes the website platform still limited to the role of a provider of travel information, and it can't provide the appropriate itinerary by understanding the needs of tourists. Therefore, for users with different travel preferences, the system will gradually plan the travel itinerary according to their record description and interaction process, and select a complete travel itinerary, corresponding to the next trip plan.

The factors that Japanese tourists are willing to choose hot spring hotels are divided into three categories. The first is hygienic and clean hot spring facilities. The second is complete fire safety facilities, and the third is hotels provide a safe leisure environment and facilities. The quality of service, the willingness to revisit, and the willingness to recommend are essential differences in the characteristics of tourists. Visitors will also consider the setting of barrier-free facilities and the complete of fire-fighting equipment as a factor in choosing a hotel. It can be seen that tourists are not only required to improve the quality of accommodation but also become an overall improvement. If tourists can collect and filter the categories of hotels before the trip, they can reduce the conflicts with cultural and environmental factors. Therefore, if the hotel recommendation system can be reinforcement, the satisfaction of tourists and the willingness to revisit will be enhanced.

For domestic tourists, the use of employee advertisements as the brand representative is the best, but for foreign visitors, the brand representative is no different from the recommended advertising effect. Travelers may be attracted to the brand representative because of their own work experience, or because of the subjective impressions of the brand representative, such as image, type, personality, etc., to determine whether the sightseeing area matches their type. This means that if today's brand representative is a sunny and outgoing person, the fans who are also outdoor sports will score higher on the place where they endorse. On the contrary, foreigners are less affected by this because they do not understand Taiwan's famous people.

The domestic tourism market is booming, the demand for hotels and the quality of services are improved, and local international tourist hotels such as in Kaohsiung and

Hualien have been significantly affected by tourist accommodation demand. Some hotels can't keep up with the changes in the environment regarding hardware and software. Tourists will have cognitive gaps in use and affect tourist satisfaction. A good recommendation system with the popularity of the Internet is a must. The above studies have shown that whether it is a star hotel, a theme hotel, a cheap hotel, etc., the choice of hotel varies from person to person, we believe that different personality traits may affect the difference in tourists' selection of hotels. For example, the tourists with extroverted personality traits may have more sense of agreement for the theme-type hotels. Those who are more concerned about the quality of life may prefer star hotels with higher stability, while those who like early adopters may choose cheap hotels.

We believe that different tourists will have different opinions and distinct needs in the hotel selection. At this stage, hotel recommendation websites such as Agoda, TripAdvisor, Booking.com, etc., provide simple classification and filtering, such as price and environmental evaluation, traffic, etc. as a simple recommendation result. We believe that the recommended results are roughly the same, and sometimes it may not be enough to suggest a hotel that allows tourists to agree, or it may incur additional costs due to unwanted hotel facilities. Besides, the website is not very interactive with tourists, so the hotel website is considered to be a platform for providing hotel information, making it difficult to understand the needs of tourists and provide suitable hotels for them. We know that the personal characteristics of tourists will have different opinions on the choice of hotels, so we hope to recommend people who like to travel, advise them to some hotels as a pocket list. If they have more opportunities in the future, they can make choices based on the pocket list.

In today's highly competitive hotel industry, if you do not take into account the real needs of tourists, you can't satisfy tourists and create word of mouth. Hotel recommendation itself is a sophisticated service. How to analyze tourist preferences and hotel type matching is a good recommendation system must pay attention. Therefore, this study combines tourist location and collaborative filtering recommendation algorithm to explore the ratings of different types of hotels by different tourists and analyze the hotels that meet the individual tourists to make recommendations to achieve the purpose of hotel recommendation.

2 Related Work

The recommendation system is based on the user's personal needs and preferences, assisting in the process of searching for a significant amount of information [2]. It uses the knowledge of an expert or a large number of users to find what you need. It is also an application for personalization problems. It is widely used in smart network systems to remove spam and provide consumer filtered information quickly. We review many large e-commerce websites, all of which are systematic recommendation models.

The primary purpose of information filtering is to filter out the information you want so that users can access and use it in a natural way [3]. More and more Internet companies such as eBay, Amazon.com, Lotte, etc. use online recommendation systems for movies, music, books, web pages and other related products. The recommendation system will filter out the desired content when the consumer browses the comprehensive information according to the user's browsing preferences. If the system can accurately predict the consumer's choice for the purchased product, the transaction volume may be increased to achieve a win-win goal.

The recommendation system can be divided into three main categories depending on the recommended method of use: content-based filtering, collaborative filtering, and hybrid approach. The recommendation system has been widely used on the Internet to collect and store consumer preferences in an explicit or implicit manner and to identify products that meet their consumption habits quickly. Different recommendation systems focus on solving different recommendation problems. The scope includes system recommended applications, data acquisition methods, and recommended method innovations, etc. The following is a detailed introduction to approach recommendation system.

2.1 Content-Based Filtering

The content-based recommendation system is derived from the use of information. It works by collecting consumer habits, such as contents that have been browsed, and the attributes of the element, e.g., like keywords or idioms, to analyze user information. Each product has its attribute string, and the collection of products is a collection of attribute strings. It is built in the database value to represent the user's profile (user profile). Briefly, it is based on the attributes and content of the item to find related products in the database to make recommendations. For example, the consumer uses the recommended service for renting online movies. The content-based filtering system analyzes the types of related videos that the customer has previously rented, and then selects the videos with higher similarity to the users.

The recommendation system is based on the analysis of the content of the item when giving information, rather than the evaluation of the person's product. The recommendation system is based on the analysis of the content of the item when presenting information, instead of people's assessment of their products. It means that the product is recommended for the listed content traits, and it also gives users confidence in the recommendation system and perspectives on their own preferences. The content-based recommendation system calculates the consumer's preference for the product, and then passes the value to the prediction module to calculate the product that is of interest to him. Mooney and Roy [4] proposed a content-based book recommendation system, which uses Information extraction and machine learning to classify text and record the user's preference weight for each text, then use this preference to achieve the purpose of recommendation.

2.2 Collaborative Filtering

Collaborative recommendation operation is to use the group's point of view to recommending the item to the user. By recording and comparing the user's preference information about the product or service, the user divides into different clusters, and each cluster is a highly relevant user. In 1992, the first Tapestry system developed by Goldberg et al. [5], its concept was to be annotated by the user to read the electronic files. When other users query, it will filter out the data in the system according to the query conditions to make recommendations. For example, A and B are lovers of love stories. One day, A saw a love story and felt very good and left a positive comment. When B wants to read a love story one day, the system will give priority to recommending this book to him. Thus, it is increasing the possibility that B will read the novel, and this way has the opportunity to achieve the recommended effect.

Resnick et al. [6] proposes that collaborative filtering is based on the behavioral perspective of the surrounding or group, and seeks users with the same experience or opinions as the basis for personalized information. Dhillon [7] divides users into different clusters by recording and comparing data using product or service preferences, each of which is a more relevant user. Therefore, the collaborative recommendation system can effectively aggregate similar groups of attributes or preferences, and then provide samples to users in the same group as a reference to meet the basis of people usually refer to others before making decisions. The primary structure is as follows: First, use the product rating provided by the customer to establish the user usage situation, and then find a similar user group from the customer group, which can also be called the nearest neighbors. Therefore, the purchased product can be introduced to the target customer by other members of the same group.

Collaborative recommendation uses other users' experience in using the product to make a rating threshold. If the rating exceeds the system's setting conditions, it will be recommended to the user. However, if the number of samples that have not been evaluated or evaluated is too few, useful recommendations cannot be made, so this recommended method applies to popular products [4]. However, if it is a brand new product, it cannot be effectively recommended by using the collaborative recommendation method.

2.3 Hybrid Approach Recommendation

Hybrid approach recommendations, as the name implies, combine two or more selection mechanisms. Collaborative recommendations can't achieve accurate predictions, only recommendations for similar users' preferences, without reference to the common preferences of similar users and target users. Therefore, a hybrid recommendation technique is proposed, which uses collaborative filtering to find users with similar preferences, and then uses content-based guidance to analyze the common preferences of users and target users to recommend items that match their preferences.

Kim et al. [8] analyze the two main types of hybrids in today's technology – sequential combination and linear combination. The sequential combination, this type of recommendation system is mainly divided into two steps. Firstly, content filtering method first finds users with the same preferences or similar. Then, it makes predictions through collaborative filtering. Linear combination, the recommended system of this type is RAAP and Fab filtering systems, which can help consumers to classify different areas of information on the network, and then recommend the URLs of the website to interested users. Fab uses content-based filtering to replace the user's rating file, so the quality of the recommendation is entirely dependent on the content filtering technology. Besides, the hybrid recommendation system method can be divided into two categories as follows:

The first is to combine individual recommendation results, mainly to mix two or more recommendation methods. Ahmad Wasfi [9] has proposed the system Profbuilder, which uses a collaborative and content recommendation system to generate two different lists. Content-based is mainly for users to browse the website page, and recommend similar websites according to the content of the website and user preferences. The collaborative filtering method is to compare the path analysis of the browsing path of the neighboring user for the user to browse the website path and recommend the related website for the user. Besides, Claypool et al. [10] also proposed the Personal Tango system, which separates the content-oriented recommendation and the collaborative recommendation method, and the degree of recommendation is the two multiplied by individual weights.

The second is to combine the two recommended methods to produce a set of recommendation results, and Fab is a typical hybrid recommendation system proposed by Balabanović and Shoham [11]. It combines content-oriented and collaborative filtering in two different ways, recommending favorite articles for readers on the website, recording each reader's preferences in detail, and finding similar readers, and then recommending articles with collaborative filtering recommendation techniques to a reader, this method is more accurate than any single recommendation.

3 Methodology

In 2001, Sarwar et al. [12] proposed Item-Based Collaborative Filtering Algorithms. Item-Based Collaborative Filtering is used to estimate the similarity to be calculated by calculating the similarity between various items. It has an underlying assumption that items that generate user interest must be similar to items with higher ratings before. It first calculates the similarity between the items that have been evaluated and the items to be predicted and uses the similarity as the weight to weight the scores of the items that have been evaluated to obtain the expected value of the items to be measured. For example, to perform similarity calculations for item A and item B, first, it finds out the item A and item B have rated at the same time. Then, it works a similarity calculation on these combinations and uses user-based collaboration filter to do the operation.

The advantage of item-based collaborative filtering is that it does not need to consider the differences between users, nor does it need to use the user's historical data to perform user identification. For the items, the similarity between them is relatively stable, so the similarity calculation step with large workload can be completed offline, thus reducing the amount of online calculation and improving the recommendation efficiency, especially when the user is more than the item. There are more than 60 methods for calculating similarity and increasing. It commonly used and well-known methods include, Persons Correlation Coefficient, Cosine-based Similarity, Adjusted Cosine Similarity and Euclidean Distance, etc.

In this system, we first use the mobile device to obtain the location of the tourist and find the location of the nearby hotel, and then we use the item-based collaborative filtering method to conduct the recommendation analysis and finally recommend several nearby hotels to provide tourist choice. The system architecture diagram is shown in the figure. In the process of recommending analysis, we take into account the impact of tourists' habits on rating score, such as the rating score is too low or the rating score is too high. Therefore, the recommendation result may be inaccurate due to such a difference. Consequently, we use adjusted cosine similarities for analysis. We take into account the impact of tourist scoring habits, and for every tourist, it will be avoided by tourist evaluate score of each hotel subtracting the average tourist evaluate score of all hotels. The final result is the similarity between the two hotels, which will get between −1 and 1. Using the user's average rating, adjust each user's rating tendency to get a more consistent similarity calculation result, the formula is as follows:

$$\mathrm{sim}(i, j) = \frac{\Sigma_{u \in U}(R_{u,i} - \bar{R}_u)(R_{u,j} - \bar{R}_u)}{\sqrt{\Sigma_{u \in U}(R_{u,i} - \bar{R}_u)^2}\sqrt{\Sigma_{u \in U}(R_{u,j} - \bar{R}_u)^2}} \tag{1}$$

where sim(i, j) represents the similarity between hotel i and hotel j. $R_{u,i}$ represents the rating of tourist u on hotel i. $R_{u,j}$ represents the rating of tourist u on hotel j. $\bar{R}_u$ denotes the average rating given by tourists to all hotels. U represents a set of tourists who have rated hotel i and hotel j (Table 1).

Table 1. The scores of rated hotels by all tourists.

	Hotel 1	Hotel 2	Hotel 3	Hotel 4	Hotel 5	Hotel 6
Tourist 1	1	5	1	2	2	4
Tourist 2	3	3	0	3	2	4
Tourist 3	3	0	2	0	2	2
Tourist 4	2	5	2	0	0	2
Tourist 5	0	3	0	0	0	5
Tourist 6	0	3	1	5	1	4

In the following table, for example, if we want to predict the rating of the tourist 2 to the hotel 3, the similarity to the hotel 3 must be calculated for all the hotels, and the similarity calculations of the hotel 5 and the hotel 3 are as follows:

$$\bar{R}_u = (3 + 3 + 0 + 3 + 2 + 4)/5 = 3)$$

$$\mathrm{sim}(\mathrm{Hotel5, Hotel\ 3}) = \frac{[(2-3)(1-3) + (2-3)(2-3) + (1-3)(1-3)]}{\sqrt{(2-3)^2 + (2-3)^2 + (1-3)^2}\sqrt{(1-3)^2 + (2-3)^2 + (1-3)^2}} \approx 0.953$$

After calculating the similarity between the hotels, the next is to make predictions for hotels that have not yet been scored, and the prediction method uses the weighted sum method to make predictions. The weighted sum is a weighted summation of the hotels that have been scored by the tourists. The obtained weight is the similarity between each hotel and the hotel i, and then the average sum of all similarities is calculated. The rating of tourist u on hotel i is as follows:

$$P_{u,i} = \frac{\sum_{j \in N}(S_{i,j} * R_{u,j})}{\sum_{j \in N}(|S_{i,j}|)} \tag{2}$$

where N denotes a set of hotels with the highest similar degree to hotel i. $S_{i,j}$ denotes the similarity between hotel i and hotel j. $R_{u,j}$ denotes the rating of tourist u to hotel j.

Taking the example above just as an example, suppose we currently want to predict the rating of the tourist 2 to the hotel 3, it uses the similarity formula to calculate the hotel 1, and the hotel 5 is the most similar to the hotel 3, with similarities of 0.913 and 0.953 respectively. Therefore, the final prediction score $P_{u,i} = \frac{(0.913*3 + 0.953*2)}{(0.913 + 0.953)} \approx 2.5$, where $P_{u,i}$ represents the predicted tourist u's rating score on hotel i.

4 Results

We use the questionnaire to collect data and analyze the tourists' overall satisfaction with the hotel and analyze and count the satisfaction. The results are shown in Figs. 1, 2 and 3. The data is built into a database and provided to the recommendation module. We use the mobile device to obtain the tourists' location and combined with the system's recommendation system. Finally, we can calculate the tourist's score for the hotel that has not yet been scored, and recommend the hotel with the higher predicted score to the tourist for reference.

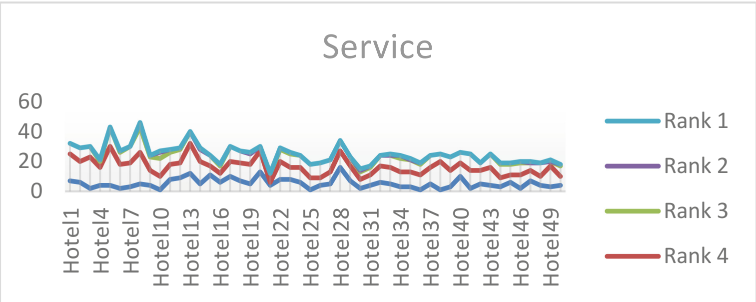

Fig. 1. The score of hotel in service

The system calculates the similarity between the hotel where the tourist has lived and the hotel that tourist has not lived. The similarity will be between −1 and 1. The closer the value is to 1, the more similar the two hotels are. Next, the tourist can enter the lowest similarity, which means to determine the similarity of the hotel you want to find. The system begins performing the calculation of the predicted values and displays the most appropriate results on the mobile device. When the value of the input similarity is too high, the system cannot successfully calculate the predicted recommendation score, and the value of the lowest similarity needs to be adjusted downward.

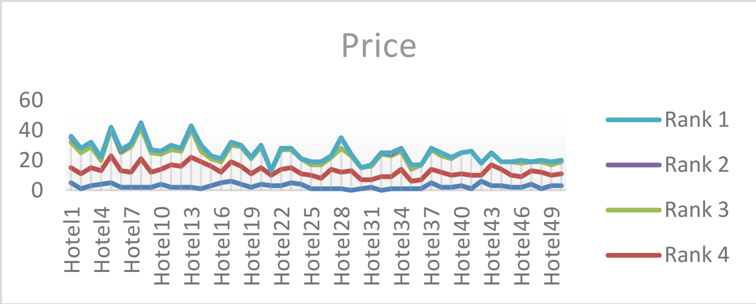

Fig. 2. The score of hotel in price

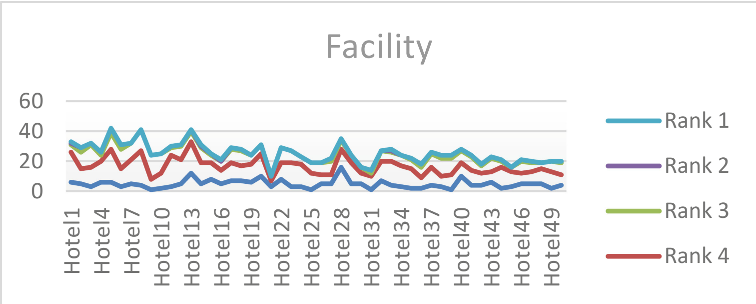

Fig. 3. The score of hotel in facility

Taking the Fig. 2 as an example, in the rating of Hotel 8, most passengers gave a score of three and four points, which is very similar to the rating of Hotel 5. Therefore, we take tourist A as an example. He has stayed at the hotel 5, and he has given a score of 4, but he has not stayed at the hotel 8. We predict that the score will be quite close. Consequently, in the system, the average score of each tourists' hotel is obtained, and then the lowest similarity is entered and brought into the system, and the predicted score is 4 points, which is similar to our predicted score. Hence, we believe that users will have similar ratings for hotels in close or similar ratings.

5 Conclusion

As the economy grows, tourists begin to pay attention to hotels. The hotel makes a more detailed distinction, and the hotel has started to make changes in various services or facilities, unlike the services that used to provide accommodation only. The Internet is the most direct source of information search for tourists, but fake messages often confuse tourists. Therefore, the recommendation system is more important, but the recommendation system now makes recommendations based on some simple factors. Therefore, this study proposes a hotel recommendation system based on user location and item-based collaborative filtering recommendation. It uses hotel similarity and prediction formulas to count the hotels that tourists have never stayed in and calculate how much they might like. Besides, this study takes the functionality of the hotel as a consideration and analyzes the three factors, services, prices, and facilities, that consumers pay most attention to. According to the tourist's rating of staying at the hotel, it makes recommendations based on the ratings of other tourists who like similar types of hotels, and hope to find the right hotel as a pocket list.

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