The Tourist Attractions Recommender System for Bangkok Thailand

Pasapitch Chujai, Jatsada Singthongchai, Surakirat Yasaga, Netirak Suratthara, and Khatthaliya Buranakutti

Abstract—**The objective of this research is to design and develop a tool to evaluate tourists' satisfaction with the attractions recommendation system in Bangkok, Thailand. We have four main stages for the tourist attraction recommendation system. The first stage is to fill imputed missing values with association rules and multiple imputations. The second stage is constructing the tourist attractions recommendation model by ranking the tourist attractions with a ranking method and similarity measurements based on a personal recommender system with cosine algorithm. The third stage is to design and develop the personal recommender website. And the last stage is to evaluate the personal recommender system with four measurements: accuracy, precision, f-measure, and g-mean. The experiment results from a sampling of thirty people found that the tourist attraction recommendation system can: 1) make a positive recommendation 340 times, but 105 times will not meet the needs, and 2) make a negative recommendation 708 times, but 77 times will meet the needs. The results show that the tourist attractions recommendation system has satisfactory performance and reliability with high accuracy, precision, and f-measure, and g-mean values of 85.20%, 76.40%, 78.89%, and 84.26%, respectively. In addition, it was found that the users' satisfaction towards the system was at a high level with a value of 4.60. This means that the proposed tourist attractions recommendation system can be used to recommend personal preferences as well.**

Index Terms—**Tourist attractions recommendation system, cosine similarity, association rule, imputed missing value.**

I. Introduction

The tourism business is a business that consumers search for information and use search engine services for searching information easily and quickly. A study of internet users' behavior in 37 countries, such as the United States, England, and France found that the consumers prefer to book accommodations, tours, air tickets as the top three products and services that can make the highest income. In addition, the World Tourism Organization (WTO) forecasted the growth of tourism in the year 2020 to be 1,561 million people, equivalent to a growth of 4.1 %, and in East Asia and the Pacific an increase of 6.5 %, and 6.7%, respectively. The tourism business is likely to grow continuously, the result is that in each country people start seeing the importance to adapt to present information and recommendations for tourist attractions. Mostly, tourists often encounter problems in planning before traveling to unfamiliar destinations. Planning a trip will be the same every time, starting with gathering information about the place, select the desired destinations, then arrange a tour schedule, and finally find the appropriate route. Although nowadays the tourists can find a lot of information available from the internet, still there are thousands of information coming from a variety of formats and multiple sources, this is why gathering information is very much time consuming. Moreover, the amount of information has a lot of effect on the decision how to choose a suitable and appropriate tourist destination. According to the research on recommendation of tourist attractions, it was found that the presentation of tourist information that considers the preferences and characteristics of tourist attractions that are suitable for each tourist is still low, which can be found in some of the researches [1]-[3]. In Kittidachanupap research [4], he explained that the website recommends that tourist attractions should be grouped according to different aspects of tourism and present the same content to all tourists. In fact, the scope of recommended attractions such as the guidance is too wide. Herlocker *et al.* [5] address the techniques for introducing popular tourist destinations used in a variety of ways such as clustering techniques, classification techniques, cosine similarity measurement techniques, and ranking techniques. But the most successful technique is the collaborative filtering (CF). CF technique is a guide to attractions from tourist information that tourists have expressed for attractions and they have visited in the past [6]. In Ricci and Missier research [6], they explained that the decision to choose specific tourist attractions depends on their personal experiences and characteristics of information. Personal information characteristics include gender, age, occupation, and income, while the tourism characteristics consist of travelers, travel characteristics, accommodation types, budget per day, and location.

Based on the problems and importance of the issues above mentioned, this research has applied the characteristics of individual preferences and ratings of users to design and develop tourist attractions recommendation systems. The objective of this research is to design, develop and evaluate tourists' satisfaction with the tourist attractions recommendation system in Bangkok, Thailand.

II. Background and Related Works

A. Recommender System

Recommended system [7], [8] is a tool or technique that provides guidance to users. Those recommendations will be

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based on the assumption of learning information, preferences or needs at the time when the user will seek them and will use them to take various decisions such as buying products, music selection for listening, or online news for reading. For this purpose, the well-known website used by recommender system to recommend users to buy books, CD or other products is Amazon.com. For popular recommendation techniques, there are three techniques: Collaborative Filtering, Content-Based, and Hybrid Approaches [9]. Collaborative Filtering approach [10] is the introduction of information or opinions of users in the previous system as a reference to predict what the new user likes or is most interested in. This technique is recommended when using vast information in the system similar or unsimilar to the users' expectations. Content-Based approach [11] recommends considering the features of the items to suggest that are similar to the features of the items that the current user has seen or used before. With this technique, the users will give feedback as a rating score. Hybrid approach [12] is a combined technique between collaborative filtering and content-based, which can reduce the limitations of both techniques, but may cause more complexity and consume more resources.

B. *Preprocessing*

In their research, Han and Kamber [13] explain that data preparation is a collection of data from many sources and also that data may come in different forms or incomplete, therefore the information obtained might not be of quality, which could result in poor quality results. If data wanted has missing values, outliers, or if data is inconsistent, if data is not in a form that can be processed, it has to be properly gathered before processing.

C. *Association Rule and Multiple Imputation*

Association rule [14] is a technique of data mining that searches for relationships, of data from large database and then finds patterns that occur frequently, to analyze relationships or predict various phenomena of unknown information. The database used in mining is a transaction database and the results are a relationship rule that can be written in the form of a cause and effect.

For the replacement of missing data by accepting the uncertainty of the value used instead, there are a variety of methods, one of which is the multiple imputation method [15]. This method will replace the missing values under the terms of the distribution of random missing data, which has three steps as follows:

The first step is using multiple regression analysis to predict the value and take that value to replace the missing data.

The second step is to analyze each data set separately in order to estimate the parameters.

The third step is to collect the results and summarize the values to replace all missing information.

III. METHOD

This research focuses on introducing personal attractions for the user who will use this recommendation system by finding similarities between the user and other tourists with cosine similarity measurement. The concept of our framework is shown in Fig. 1.

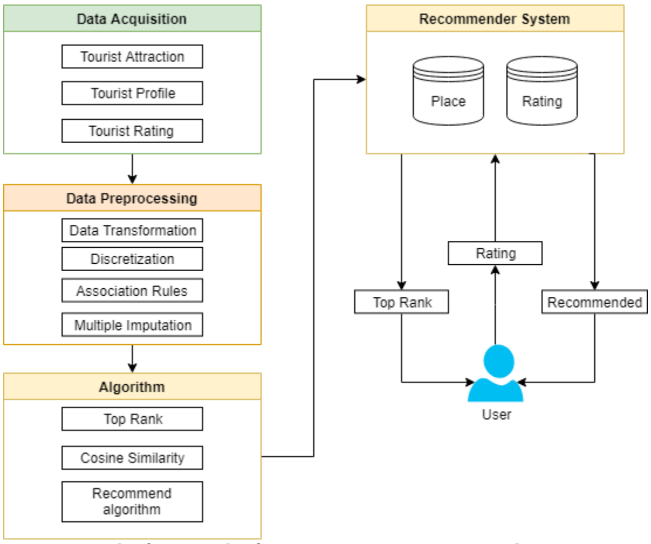


Fig. 1. The framework of tourist attractions recommender system.

Fig. 1 illustrates each step as follows.

A. *Data Acquisition*

For this step, the data collected will include tourist information, personal travel information and satisfaction scores for tourist attractions that have been visited.

B. *Data Preprocessing*

In this step, the collected data will convert the format from characters into numbers and from Thai language into English language. Some parts of raw data will be divided into the categories such as *age*, and *cost_per_trip* variable. *age* variable category will be divided into three categories and *cost_per_trip* variable will be divided into four categories. In addition, the data collected will contain some lost data as shown in Table I, the missing value being in the *rate* column.

TABLE I: DETAIL OF MISSING VALUE IN CASE CENTRAL RAMA II

No	sex	age	cost_per_trip	trip_per_m	trip_with	rate
2	female	>21.5	>1750	'1 time'	couple	
11	female	>21.5	>1750	'1 time'	friend	
17	female	20.5 - 21.5	450 - 550	'2 times'	couple	
18	male	20.5 - 21.5	550 - 1750	'1 time'	alone	
19	female	20.5 - 21.5	>1750	'1 time'	friend	
11	female	>21.5	>1750	'1 time'	friend	

Remark cost_per_trip is the cost for each trip,
trip_per_m is the quantity of trips,
trip_with is traveling companion
rate is preference score from 1 to 5: 5 is most satisfied, while 1 is least satisfied.

TABLE II: DETAIL OF COMPLETE DATA IN CASE CENTRAL RAMA II WITH RATE = 3

No	sex	age	cost_per_trip	trip_per_m	trip_with
4	male	20.5 – 21.5	550 – 1750	'3 times'	couple
7	male	20.5 – 21.5	<450	'2 times'	family
10	male	20.5 – 21.5	>1750	'1 time'	family
12	female	20.5 – 21.5	450 – 550	'2 times'	family
36	female	>21.5	450 – 550	'>3 times'	friend

TABLE III: DETAIL OF COMPLETE DATA IN CASE CENTRAL RAMA II WITH RATE = 4

No	sex	age	cost_per_trip	trip_per_m	trip_with
5	female	20.5 – 21.5	<450	'1 time'	friend
8	female	20.5 – 21.5	<450	'1 time'	friend
9	male	>21.5	450 – 550	'1 time'	friend
16	male	20.5 – 21.5	450 – 550	'2 times'	couple
23	female	>21.5	>1750	'2 times'	couple

TABLE IV: DETAIL OF COMPLETE DATA IN CASE CENTRAL RAMA II WITH RATE = 5

No	sex	age	cost_per_trip	trip_per_m	trip_with
1	male	20.5 – 21.5	<450	'1 time'	couple
3	female	20.5 – 21.5	<450	'>3 times'	friend
6	male	20.5 – 21.5	>1750	'2 times'	lonely
13	male	20.5 – 21.5	550 – 1750	'2 times'	friend
14	female	20.5 – 21.5	450 – 550	'>3 times'	couple

TABLE V: DETAIL OF ASSOCIATION RULES OF RATE=3

Rule	sex	age	cost_per_trip	trip_per_m	trip_with	rate
1		<20.5		'3 times'		3
2	male	<20.5		'3 times'		3
3	male	<20.5		'3 times'		3

In this research, two techniques were used to replace missing value: replace with association rule and multiple imputation methods, details are as below.

1) Replace with association rule

In Table I, we divided the remaining data, which is not lost according to the *rate* variable, details as in Table II, III, and IV.

For association rule, we used the *Apriori* algorithm in Weka with minimum support value equal to 0.35 and minimum confidence value equal to 0.6. Finally, we chose three rules with high confidence value to replace the missing value.

Example of association rules in rate equal to three are as follows:

(a) age = <20.5 AND trip_per_m =>3 times

(b) sex = male AND trip_per_m =>3 times AND age = <20.5

(c) sex = male ANDage = <20.5 AND trip_per_m =>3 times

(d) trip_per_m = >3 times AND age = <20.5

(e) age = <20.5 AND sex = male

(f) trip_with = friend AND cost_per_trip = 450 - 550

From the above rules, we chose the best three rules from top to bottom. In the case of duplicate rules such as (b) and (c), where both rules are the same rule, we switched data from one to another, then we chose the bottom rule (c). For other groups we did the same process.

TABLE VI: DETAIL OF ASSOCIATION RULES OF RATE=4

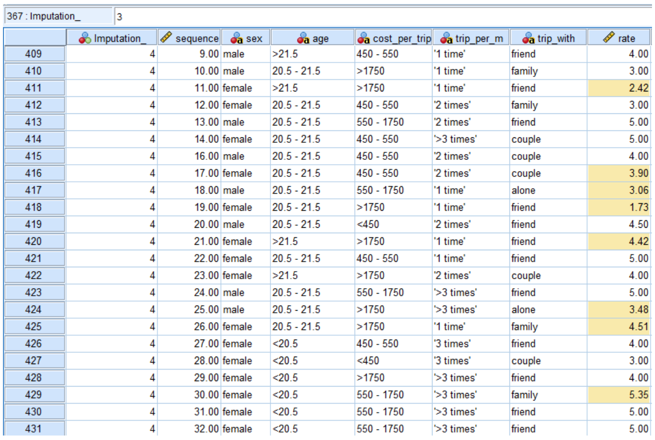
No	sex	age	cost_per_trip	trip_per_m	trip_with	rate
1	male				friend	4

TABLE VII: DETAIL OF ASSOCIATION RULES OF RATE=5

No	sex	age	cost_per_trip	trip_per_m	trip_with	rate
1		<20.5			friend	5
2	male				friend	5

TABLE VIII: DETAIL OF IMPUTATION MISSING VALUE WITH ASSOCIATION RULE

no	sex	age	cost_per_trip	trip_per_m	trip_with	Rate replacement
28	female	<20.5	<450	'3 times'	couple	3
31	female	<20.5	550 - 1750	'>3 times'	friend	5
35	male	>21.5	>1750	'1 time'	friend	4.5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	Imputation_	sequence	sex	age	cost_per_trip	trip_per_m	trip_with	rate
409	4	9.00	male	>21.5	450 - 550	'1 time'	friend	4.00
410	4	10.00	male	20.5 - 21.5	>1750	'1 time'	family	3.00
411	4	11.00	female	>21.5	>1750	'1 time'	friend	2.42
412	4	12.00	female	20.5 - 21.5	450 - 550	'2 times'	family	3.00
413	4	13.00	male	20.5 - 21.5	550 - 1750	'2 times'	friend	5.00
414	4	14.00	female	20.5 - 21.5	450 - 550	'>3 times'	couple	5.00
415	4	16.00	male	20.5 - 21.5	450 - 550	'2 times'	couple	4.00
416	4	17.00	female	20.5 - 21.5	450 - 550	'2 times'	couple	3.90
417	4	18.00	male	20.5 - 21.5	550 - 1750	'1 time'	alone	3.06
418	4	19.00	female	20.5 - 21.5	>1750	'1 time'	friend	1.73
419	4	20.00	male	20.5 - 21.5	<450	'2 times'	friend	4.50
420	4	21.00	female	>21.5	>1750	'1 time'	friend	4.42
421	4	22.00	female	20.5 - 21.5	450 - 550	'1 time'	friend	5.00
422	4	23.00	female	>21.5	>1750	'2 times'	couple	4.00
423	4	24.00	male	20.5 - 21.5	550 - 1750	'>3 times'	friend	5.00
424	4	25.00	male	20.5 - 21.5	>1750	'>3 times'	alone	3.48
425	4	26.00	female	20.5 - 21.5	>1750	'1 time'	family	4.51
426	4	27.00	female	<20.5	450 - 550	'3 times'	friend	4.00
427	4	28.00	female	<20.5	<450	'3 times'	couple	3.00
428	4	29.00	female	<20.5	>1750	'>3 times'	friend	4.00
429	4	30.00	female	<20.5	550 - 1750	'>3 times'	family	5.35
430	4	31.00	female	<20.5	550 - 1750	'>3 times'	friend	5.00
431	4	32.00	female	<20.5	550 - 1750	'>3 times'	friend	5.00

Fig. 2. Magnetization as a function of applied field.

We took data from Table I to Table IV in order to generate association rule, the results are shown in Table V to Table VII. Then we took this rule to replace missing values, the results show in Table VIII.

From Table VIII, the index no. 28 corresponds to the rule no. 1 of the group rate four (Table VI) and rule no. 2 of the group rate five (Table VII), so the new rate value equal to 3. While index no. 35 corresponds to rule no. 1 of the group rate four (Table VI), rule no. 2 corresponds to the group rate five (Table VII), therefore, the new rate value is now an average of 4.5 ((4+5)/2).

2) Replace with multiple imputation method

For multiple imputation method, we used SPSS program with imputations equal to 20, max value and min value of rate variable equal to 1 and 5, respectively. Before replacing the missing value, we are divining the group of data according to the name of the place and choosing only the attractions with votes value over 50%.

Example of data replacement with multiple imputation method is shown in Fig. 2. Then we find the accuracy with Automatic Linear Modeling of each data set, in regression statistics to find the most accurate data set.

C. Algorithm for Recommender System

1) Ranking of tourist attractions by ranking method

The ranking method [16] of tourist attractions is calculated by the average satisfaction score, by sorting out the places that have the highest average satisfaction value to the place with the least satisfaction value, as in (1).

$$\bar{x}_i = \frac{\sum x_i}{N_i} \tag{1}$$

where $\bar{x}_i$ is the average satisfaction score of place *i*.

$\sum x_i$ is the summation of average satisfaction score of place *i*.

N_i is the total number of persons who provided a satisfaction score of place *i*.

Example of the average of each location as shown in Table IX.

2) Personal tourist attractions ranking with cosine similarity measurement

Cosine similarity measurement [17] will calculate the similarity between the user and the tourists who are in the same group at that target tourist, as in (2).

$$\mathrm{Cos}(X, Y) = \frac{X * Y}{\|X\| * \|Y\|} \quad (2)$$

where $\mathrm{Cos}(X, Y)$ is similarity value

X is the preference level in each place of target tourists

Y is the preference level in each place of each tourists who are in the same group at that target tourist

$X * Y$ is $(x_1 * y_1) + (x_2 * y_2) + \cdots + (x_n * y_n)$

$\|X\|$ is $\sqrt{\sum x^2}$

$\|Y\|$ is $\sqrt{\sum y^2}$

The similarity between the first tourist and other tourists, defines the top ranking (top-K at K = 3) with the most similar values as shown in Table X. In this table, we found that the first tourist was satisfied with the tourist no. 52, with the highest score of 0.84.

In this research, users must rate their satisfaction of at least six attractions before using the recommendation system. When users give satisfaction points to tourist attractions, we use this data to find the similarity scores in order to determine which tourists are like us. Then we select the top three tourists with the highest similarity. The system considers the travel history of all three tourists then defines the places that match the users' needs. Then, the system regroups the information collected from these three people in order to find its average value and then rank it, as shown in Table XI. Finally, the system recommends the tourist attractions from the top five ranks.

TABLE IX: EXAMPLE OF THE RANKING OF TOURIST ATTRACTIONS WITH RANKING METHOD

No.	Place	Average Score
1	Snow Town	4.64
2	Nitasrattankosin	4.57
3	JJ Green	4.44
4	Jatujak Weekend Market	4.35
5	Safari World	4.35
6	Market 61	4.33

TABLE X: SHOW EXAMPLES OF SIMILARITY OF THE 1ST TRAVELER WITH OTHER TOURISTS

No.	$\mathrm{Cos}(X, Y)$	Similarity Score
1	$X_1: Y_{52}$	0.84
2	$X_1: Y_{69}$	0.59
3	$X_1: Y_{68}$	0.58

TABLE XI: SHOW EXAMPLES OF FINDING THE AVERAGE OF PLACES TO SUGGEST TOURIST ATTRACTIONS

User	1st Place	2nd Place	3rd Place	4th Place	5th Place	6th Place
1st Tourist	5	3	5	4	3	5
2nd Tourist	4	3	5	4	2	4
3rd Tourist	4	4	5	3	2	2
Average	4.33	3.33	5	3.66	2.33	3.66

IV. EXPERIMENTAL EVALUATION

A. Data Sets

The sample in this research is divided into two groups.

The first group consists of 100 people who answered the questionnaire. The questionnaire is divided into two parts. The first part is the personal information of the sample. The second part is to give a preference rating on the places that have been visited. This research is evaluating forty-three attractions.

The second group consists of 30 people who used the web tourist attractions recommendation system in Bangkok, Thailand. Each user must provide personal information and preference rating on the places that have been visited at least six places before using this website.

B. Performance Evaluation

The tourist attractions recommendation system has measured performance and reliability with four measurements [18] as follows:

True Positive Rate (TPR): $$\frac{TP}{TP + FN} \quad (3)$$

True Negative Rate (TNR): $$\frac{TN}{FP + TN} \quad (4)$$

Precision: $$\frac{TP}{TP + FP} \quad (5)$$

F-measure: $$\frac{2 * TPR * Precision}{TPR + Precision} \quad (6)$$

G-mean: $$\sqrt{TPR * TNR} \quad (7)$$

Accuracy: $$\frac{TP + TN}{(TP + FN + FP + TN)} \quad (8)$$

where *TP* is the number of attractions that users like, and the system recommends,

TN is the number of attractions that users do not like, and the system does not recommend,

FP is the number of attractions that users do not like, but the system recommends, and

FN is the number of attractions that users like, but the system doesn't recommend it.

C. Results and Analysis

For measuring the efficiency of the tourist attractions recommendation system, all users must evaluate the effectiveness of the website.

TABLE XII: DETAILED PERFORMANCE INFORMATION OF ONE USER PER TOURIST ATTRACTION RECOMMENDATION SYSTEM

Name of Attractions	Efficiency			
	TP	TN	FN	FP
1. Central Plaza Rama II	✓			
2. Pantip Plaza	✓			
3. MBK Center	✓			
4. Central World		✓		
5. Platinum				✓
6. Chatuchak Weekend Market			✓	
7. Train Night Market Srinakarin	✓			
…	…	…	…	…
43. Queen Sirikit Park		✓		
Summary	9	26	5	3

TABLE XIII: SHOW THE EFFICIENCY OF THE TOURIST ATTRACTIONS RECOMMENDATION SYSTEM

	Recommend	Not Recommend
Like	340	77
Not Like	105	708

The details of the performance of one user per recommendation system are shown in the Table XII. In this table, thirty users will completely evaluate the recommendation system, and then summarize that information in order to find the efficiency and accuracy of our model. Details of all thirty users per forty-three attractions are shown in Table XIII.

In Table XIII, we evaluate the efficiency and accuracy of the personal recommender system with four measurements: accuracy, precision, f-measure, and g-mean. The experiment provides results from the sample of thirty people; it found that our model recommends 340 times a tourist's attractions that meets the needs, 105 times it recommends a tourist's attractions that not meets the needs, 77 times it does not recommend a tourist's attractions that meets the needs, and finally, 708 times it does not recommend a tourist's attractions that does not meets the needs. Those results show that our model is efficient and reliable with high accuracy, precision, f-measure, and g-mean values respectively of 85.20%, 76.40%, 78.89%, and 84.26%. In addition, we have used the questionnaires to evaluate the users' satisfaction for the tourist attractions recommendation website. The questionnaires have two parts considering the usability of the website and the efficiency of the model. The rating scale ranges from 0 to 5, where 0 is the lowest satisfaction score and 5 is the most satisfactory score. The result shows that the satisfaction of users towards to the system was at a high level which a value of 4.60.

V. CONCLUSION

The recommender system can be applied to many services, such as recommending tourist attractions for tourists who have diverse preferences. In this case, we have adapted algorithms introducing data into the application with data mining techniques. This can be seen from our concept of using various algorithms to use for recommender system. Our model starts with the collection of data from the sample with the questionnaire. The information received was incomplete, thus we imputed missing values with association rules and multiple imputations method. Then we constructed the tourist attractions recommendation model by ranking the tourist attractions with a ranking method and similarity measurements using the personal recommender system with cosine algorithm. We then designed and developed the personal recommender website. And finally, we evaluated the personal recommender system with four measurements: accuracy, precision, f-measure, and g-mean. The results of the experiment about the tourist attractions system found that the model that we proposed is efficient and reliable, able to recommend tourist attractions to users as well. Users are also satisfied with the website at a high level. We can conclude that the proposed concept can be applied to other recommended tasks as well. In the future, we can combine our concept and new techniques from machine learning together for education recommendation system.

CONFLICT OF INTEREST

In this research, there is no conflict of interest. We declare that "The authors declare no conflict of interest".

AUTHOR CONTRIBUTIONS

The works of each author in this work are as follows:

Pasapitch Chujai and Jatsada Singthongchai are consultants and give advice about techniques, methods to be used in the process of the recommender system. Also, Pasapitch Chujai wrote the paper and oral presentation at ICACTE 2019 conference.

Surakirat Yasaga, Netirak Suratthara, and Khatthaliya Buranakutti operates in the part of collection data, recommended system development and evaluation of the system.

All authors had approved the final version.

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