INTELLIGENT TRAVEL ROUTE SUGGESTION SYSTEM BASED ON PATTERN OF TRAVEL AND DIFFICULTIES
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Abstract. People travel a lot to new places for career, business, education, travel, health and for various other reasons. Travellers always search to find shortest and safest route to reach the destination. They majorly consider distance, modes of transport and safety as major parameters. Various algorithms, mechanisms are proposed earlier to serve the purpose. However existing algorithms, mechanisms suffer from various shortcomings like unable to analyze the suggestions and filtering the database. The existing models use collaborative or content filtering algorithms. These methods do not collect the past user experience. The main objective of this paper is to help the travellers from their source to target from a database with best possible way. Proposed method provides the information from the travellers and problems faced by them during their travel. Based on the reported issues and experiences, new path will be enrooted to the destination. In the proposed model C4.5 decision tree algorithm is used to collect data from previous user experience, minimum redundancy maximum relevance (MRMR) and features selection algorithm is used to reduce execution time and increase system accuracy. The experimental outcome of this paper is to improve the system accuracy and performance.

Keywords: Recommendation System; Tourist Destination, Feature Selection; Filtering methods; Mutual information; Classification; Decision Tree.

1 INTRODUCTION
Travels and Tourism sector the role of planning effective routes is complex, dynamic and includes various decision-making factors such as quality of attraction, travel time, cost, safety, accommodation, tourist numbers, leisure activities, weather and so on. Recently, ICT and Internet technologies started playing an important role in tourism. The tourists and tour operators can review, pick, evaluate and take decisions easily by implementing decision support systems known as "Recommendation Systems" (RS). The majority of earlier Travel Route Suggestion (TRS) relied on estimations based on the user's expectations and requirements to decide the location, events, attractions, tourism facilities(for example, restaurants, hotels, transportation). Lacking in technical aspects such as (e.g. scalability, reliability, system accuracy, personalization theories etc.) and functional aspects like (e.g. customer retention, accessibility, etc.) fail. These aspects are not accessible. One of the greatest problems is increasing a TRS that provide personalized recommendations of visitor targets and develop the visitor decision-making method. In order to complete this, it needs a deep understanding of the travellers’ decision-making and develops new models form their information seeking process. In addition, the efficiency of the recommendation and the customer satisfaction level of the program can be improved. By reducing extra attributes in the system the complexity could be decreased. This paper proposes a new TRS, which suggests tourist destination to solve the difficulties mentioned. Three main developments are included in the proposed TRS. First of all, unwanted (like redundant) inputs have been eliminated and the complexity of the interface is reduced by using two feature selection methods. Secondly, a decision tree C4.5 is used as a classifier to see the traveller destination selection method. Lastly, the future method uses real world information that has been collected from Chiang Mai, Thailand [1].

The paper is majorly organized into 6 sections. Section 2 provides background on recommendation systems in the tourism domain. Section 3 describes the data collection process used in this paper. Section 4 presents the proposed TRS framework using the DM approach. The experiment setup for this study is demonstrated in Section 5. Section 6 shows the results and the evaluation analysis of the proposed TRS. Finally, presented some tentative conclusion and future scope of this work.

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2. LITERATURE SURVEY

Travellers choose a destination based on tourist or traveller guide. Thailand Annual Report 2013 stated that, the individual demographics that influence the actions are identified. 4,000 Information-seeking Questionnaires are distributed and collected in five tourist destinations of Chiang Mai, Thailand. The favourite destinations lists were taken from the website of the Trip Advisor. All worldwide (60%) and domestic tourists (40%) participated in the study. The data pre-processing phase was assisted by 3,696 valid questionnaires and 146 variables, although 35 samples not fully supplied. The task includes artificial intelligence to study from travellers’ knowledge and to use this information to direct future travellers to their own destination. You may also sell similar videos by using this form for a video watchmaker based on the tickets that you previously booked. Therefore, one of the previous visitor meetings and one of the patterns will be taught two times by the actual consumer. An-Jung Cheng et al [2] proposed travel route recommendation based on photographic elements such as gender, time, and event. People attributes are useful for making decisions on travel landmarks and paths and also helpful for route planning and personalized travel recommendation. The development of recommendation systems is based on user interests. Social data, including check-in behaviour, social contacts, feedback and recent studies, lead to making highly accurate travel recommendations. The author provides a site advisory programmer: the UI module, the idea module, the rating module and the Location Based Social Network (LBSN). The position scores are 0 to 1 value and are used by a recommendation application to match the LBSN data with the user attributes. Pantano et al proposed a way to plan a trip using the history of Flickr[3][4]. The author suggests a photographer behaviour model path, which estimates the probability of the photographers visit. Ge Cui et al. [5] propose two approaches. [6, 7, 8, 9] is the two form of collaborative travel route recommendation are collaborative travel route recommendation CTRR, and an expanded version of CTRR. Both methods employ personalized routes followed by GPS-based users. Users are calculated using collaborative filtering techniques to optimize travelling speeds and to achieve the greatest likelihood of travel using the Naive Bayes model [10, 11, 12, 13].

3 PROPOSED SYSTEM

Choosing a tourist destination using the information available on internet and from other sources is one of the difficult tasks for visitors in tour planning before and during trips. In order to solve this problem TRSs is proposed earlier. However, some of the system accuracy, usability and satisfaction have been ignored. In order to solve this issue, it needs a full understanding of the visitor’s decision-making and new models of the process of seeking information. This paper proposes C4.5 decision tree algorithms which take experiences of previous users and then build a model. Users provide their requirements to the system, and then decision tree will predict best location based on his given input. Sometimes datasets will have empty or garbage values and gives bad effect on decision tree model. It can be eliminated by applying pre-process techniques. To predict or build model no need to use all attributes values from dataset and this unnecessary attributes can be eliminated by applying features selection algorithms.

4 METHODOLOGIES

The process of identifying tourist destination is done through C4.5 decision tree approach. The suggested approach uses data from the real world from Chiang Mai, Thailand.

4.1 Recommendation system

A suggestion framework RS, a subset of Decision Support Systems (DSS), is a technique that can suggest an item based data collected for the user preferences [14,22]. It helps customers to make decisions based on their preferences and concerns by providing them with helpful information. RS
plays a significant job and is common in popular online business sites, for example, Amazon, Netflix, Pandora, and so forth [15, 16]. The web based business RSs recommend item to the client which includes news, papers, individuals, URLs, etc[17, 21].

4.2 Systems of Travel Advisory

Tourism is a leisure activity and difficult to make decision processes, for example, the choice of destinations, attractions, events and services. So many researchers in both academic and industry receive a TRS attention. Different TRSs (e.g. web, browser, mobile) have been developed in and on several platforms. For the purposes of assessing user interest, TRS suggest results to customer for use the of user preferences, selecting point of interest (POIs), defining or classifying services or routes or as a holistic journey. Most of the existing TRSs aim is to help single tourist, there are some systems that support travel agencies as well. They share similar structures but vary in the choice of technologies, personalization philosophies, data inputs, types of interaction and suggestion techniques. Data is embedded in and keyed in the server from many resources (e.g. sensors, GPS, surveys, comments etc.). The recommendation engine may consist of a several subsystems, including an optimization subsystem, a numerical subsystem and an intelligent subsystem, etc. In general, before and during the journey, most TRSs are used to display the end result. Fig 1 shows framework of travel route recommendation systems.

4.3 Recommendation techniques

The effectiveness and consistency of the proposed technique can be measured by the degree of personalization. This can be designed from low to high, with non personalization, short term customization and long term customization. The non-customized RS is a very simple program that does not come into account user needs when making suggestions. For example, the RS produces only a list of the common products based on the number of transactions or reviews. Customized RS has been progressed more than a non-customized RS due to its limited decision-making ability. This means that each user will see another set of guidelines, according to his / her preferences. For
example, a target based on user socio demographic information is being suggested by tour-advisors. In addition, several forms of Personalized RSs have been classified and analyzed in previous studies using the method of information filters. In the next section, we will briefly investigate the recommendation engine Fig.2 which is composed of several recommendation techniques based on findings.

![Recommendation Engine Diagram](image)

**Fig.2. Recommendation Engine**

4.3.1. **Collaborative filtering:** This approach is widely adopted by the most implemented recommendation systems. It suggests the items to the customer based on comments given by new visitors, who distribute the same features. There is an issue with a cold-start approach [18], which will have to be classified before a new item or consumer would make a suggestion.

4.3.2. **Content-based filtering:** This technique suggests items to the user based on his/her previous searches or queries for items. The main drawback is the cold-start problem for the user, where the user wants to present a lot of information earlier than a decision can be made. Another popular trouble is over-expectation, as the method would most probably recommend the item was mainly liked by the user with less variance, the quality results are produced through the archive of extensive historical data set [19].

4.3.3. **Knowledge-based filtering:** Based on domain awareness this recommends the items to the user. In other words, the system has some data of how the particular item relates to a particular customer. Predominantly, this method can be achieved by using case-based analysis or ontological methods [20]. This suggestion technique is designed to benefit from past experiences between travel agencies and groups.

4.3.4. **Hybrid filtering:** The following technique has some strengths and limitations. The purpose of the hybrid recommendation technique is to achieve the best performance and to remove the weaknesses/disadvantages of one technique by complementing (which technique rewrite the sentence) it with the advantages of another. Many hybridization methods are also possible, for example by combining weight, flip page, mixture, function combinations, cascades, feature increases and metric rates.

4.3.5. **Methods**

1) the frequencies of user visits to different destinations the program will begin learning from scratch. The most popular destinations can be categorized and shown to the visitor, indicating that he / she travels to the most commonly visited spot. This program will slowly follow the needs of a consumer who visits somewhere else. Therefore, for training the program in two classes, it requires a machine learning algorithm similar and different destinations. The number of visitors to each other can be counted and averaged from one source to both locations by complete tourists. This counter will then have a value of 0 to 1. 1 if the same people visit both locations. 0 if the same people do not visit two
locations. The user’s favourite routes from his travel experience are based on this similarity score system.

(II) The program can also calculate the difficulties in any direction based on a comment of users and forecast a route that is complex or simple to achieve from feedback score (1-5) from visitors to these sites. Use of these scores can alert users of difficult routes. Once the next visitor enters the program, the previous score and number of visitors will be updated to get a new ranking. The program can also be educated on the basis of texts on the traveller’s path. When the route is considered to be complicated, the findings can be preserved in a chart concerning the trip. This can be saved as a nice ride on a smooth and fun route. This method can then be regressed logistically to teach the input nodes identical to the possible amount of terms in a sentence, say 100. For each one, the input and output of which document class are complex and which class are nice can be identified and supplied to the Neural Network. It immediately takes a challenging or simple trip, when we offer a new feedback on place travellers. Unlike this person, any chosen route may display different rates. Any route's complexity can be educated using input parameters such as:

1. Road conditions
2. Weather conditions
3. Transport
4. Number of accidents
5. Human personality (e.g. age, individual gender)

A controlled approach is training on routes that are already established as difficult and easy. 3-4-layer network can be used for this project with each parameter between 0 and 1 in value.

5 EXPERIMENTAL PROCESSES

I. Road suggestion based on travel guide

Phase 1: To store the number of visitors to destinations, a database is developed.

Phase 2: The user can choose between the number of visits and the device.

Phase 3: The similarity score is determined from a database on a pair of routes that are separated by the total number of visitors to each route.

Phase 4: Based on traveller’s history related routes are displayed for choosing next targets

The fig 3 is road suggestion based on travel guide

Fig. 3. Route suggestion based on travel guide of other user history
II. The complexity path to the user

Phase 1: Store visitor difficulty input in a score (1-5) and/or input text for all routes in the database.
Phase 2: Compute the problem score by dividing score by total guests. Apply 1 to the number of problems and change the problem score each time.
Phase 3: Train a neural network for traveller textual feedback to predict routes that are difficult and successful.
Phase 4: Show new users both the challenge and their simple understanding of the difficulties of travelling. The fig 4 knows the difficulty of a route

![Diagram](image)

Figure 4. Knows the Difficulty of a route

**Measures for assessment:**

- Latest ways is based on travel habits of others and visitor’s history are shown properly.
- For known difficult paths, a high difficulty score is correctly displayed.
- Below are the columns or attributes of the dataset used by previous users.

This collection of data is complemented by TripAdvisor.com crawling. Reviews are considered on destinations in 10 groups in East Europe. -- Rating is classified as Excellent (4), Really Good (3), Great (2), bad (1) and Terrible (0). -- Group is labeled with average ratings per user.

**Columns and meanings of the data set**

Theatres, religious establishments, venue, user ids, gallery-art, salsa clubs, liquid bars, restaurants, museums, spa, place and picnic spots.

The column names above and the column values below are

User1,0.93,1.8,2.9,0.62,0.8,2.42,3.19,2.79,1.8,2.42,Amsterdam_Heining_2
User2,1.02,2.2,2.66,0.64,1.42,3.18,3.21,2.63,1.86,2.32,Amsterdam_Jachthaven_ijbur
User3,1.22,0.8,0.54,0.53,0.24,1.54,3.18,2.8,1.31,2.5,Amsterdam_Bert_Haanstra_Kad
For each user, the meaning of the first column is USER ID and the second column is ART GALLERIES. The third column is DANCE CLUB etc.

Now using above values we can build C4.5 decision tree and prediction will be done using below test values

'User 122', 0.93, 1.8, 2.29, 0.62, 0.8, 2.42, 3.19, 2.79, 1.82, 2.42,
'User 222', 1.02, 2.2, 2.66, 0.64, 1.42, 3.18, 3.21, 2.63, 1.86, 2.32,
'User 3222', 1.22, 0.8, 0.54, 0.53, 0.24, 1.54, 3.18, 2.8, 1.31, 2.5,
'User 4222', 0.45, 1.8, 0.29, 0.57, 0.46, 1.52, 3.18, 2.96, 1.57, 2.86,
'User 522', 0.51, 1.2, 1.18, 0.57, 1.54, 2.02, 3.18, 2.78, 1.18, 2.54,

New users have provided new test values for location with above-average ratings but new users don't know where such services are available, so when we upload test values into the decision tree they determine so predict the user's best position and notify him.

**6 EXPERIMENTAL RESULTS**

![Fig. 5. Upload tourist data package](image-url)

In the above tab press the button "Upload tourist data package" after uploading, all the data set information are given below the screen (write in detail)
Fig. 6. Displaying Datasets of Previous Users Experiences

The above screen contains all users that have been loaded with the previous experience and a total of 12 attributes.
To delete empty values and reduce the size of attributes, press 'Run Pre-process Selection Algorithm'.

Figure- 7. Displaying the Selection Feature Attributes

All those attributes which have column TRUE and column FALSE are ignored in the above screen after applying the MRMR scope size to 3.
Click on the "Template Tree for Generating C4.5 Decision"
We can see in the above screen the models created by the IF and ELSE declaration tree. If > any decision will be made, if < another decision will be selected. Click on the 'Tourist Recommendation' button to upload the test file without the place name.

I have uploaded the test file on above screen and now click on open to get the location that I suggest. In the name of the test file, there is no appeal.
Once the test data are uploaded, all the values are in the test data but the position name and base on the application of the test values are predicted or the place name is not suggested in the above screen.

Figure- 10. Test Files

Click the Set of Features button below the diagram

Figure- 11. Feature Selection Graph

In the Figure-11. the x-axis is total characteristics are shown and the MRMR selected and y-axis is countless and in above graph the size of characteristics decreases to 3 after the application of the MRMR technique

7 CONCLUSION

This Paper proposes a decision tree based visitor recommendation method to address the existing TRS problem. The data set was broken down into two subsets using specific knowledge of the tourism. This is used in order to increase the system accuracy and to decrease the decision tree complexity. The optimal decision trees of NMIFS were optimized for the option of the destination, with the maximum precision and ease (i.e. less leaf and tree sizes). Decision guidelines derived from decision-making bodies. The NMIFS is the optimum method because it uses less number of features than MRMR for both of the data sets. Finally, the test results indicate that the proposed decision tree is valid. The proposed decision tree satisfies the travellers’ requirements who plan to visit or during their visit the city. In addition, different types of classifiers can be considered to increase the classification accuracy rate for the data sets. Moreover, front-end web application and an interactive and adaptive user interface will be designed and implemented.
REFERENCES

[1] “Economic Impact of Travel & Tourism 2014 Annual Update: Summary.” World travel & tourism council. “Thailand Annual Report 2013.”

[2] Personalized Travel Recommendation by Mining People Attributes from Community-Contributed Photos, An-Jung Cheng et al., Copyright 2011 ACM 978-1-4503-0616-4/11/11

[3] E. Pantano and L. D. Pietro, “From e-tourism to f-tourism: emerging issues from negative tourists’ online reviews,” J. Hosp. Tour. Technol., vol. 4, no. 3, pp. 211–227, 2013.

[4] B. Pan and D. R. Fesenmaier, “Semantics of Online Tourism and Travel Information Search on the Internet: A Preliminary Study,” Inf. Commun. Technol. Tour. 2002 Proc. Int. Conf. Innsbr. Austria 2002, pp. 320–328, Jan. 2002.

[5] Personalized travel route recommendation using collaborative filtering based on GPS trajectories, Ge Cui, Jun Luo & Xin Wang, International Journal of Digital Earth Volume 11, 2018 -Issue 3

[6] E. Pitoska, “E-Tourism: The Use of Internet and Information and Communication Technologies in Tourism: The Case of Hotel Units in Peripheral Areas,” Tour. South East Eur., vol. 2, pp. 335–344, Dec. 2013.

[7] Maheswari, V. Uma, G. Varaprasad, and S. Viswanadha Raju. "Local Directional Maximum Edge Patterns for facial expression recognition." Journal of Ambient Intelligence and Humanized Computing (2020): 1-9.

[8] G. Häubl and V. Trifts, “Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids,” Mark. Sci., vol. 19, no. 1, p. 4, Winter 2000.

[9] F. Ricci, L. Rokach, and B. Shapira, “Introduction to Recommender Systems Handbook,” in Recommender Systems Handbook, F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, Eds. Springer US, 2011, pp. 1–35.

[10] P. Resnick and H. R. Varian, “Recommender Systems,” Commun ACM, vol. 40, no. 3, pp. 56–58, Mar. 1997.

[11] G. I. Alptekin and G. Buyukozkan, “An integrated case-based reasoning and MCDM system for Web based tourism destination planning,” EXPERT Syst. Appl., vol. 38, pp. 2125–2132, 2011.

[12] R. Anacleto, L. Figueiredo, A. Almeida, and P. Novais, “Mobile application to provide personalized sightseeing tours,” J. Netw. Comput. Appl., vol. 41, pp. 56–64, May 2014.

[13] L. Sebastia, I. Garcia, E. Onaindia, and C. Guzman, “e-TOURISM:: A TOURIST RECOMMENDATION AND PLANNING APPLICATION,” Int. J. Artif. Intell. Tools, vol. 18, no. 5, pp. 717–738, Oct. 2009.

[14] J. B. Schafer, J. A. Konstan, and J. Riedl, “E-Commerce Recommendation Applications,” in Applications of Data Mining to Electronic Commerce, R. Kohavi and F. Provost, Eds. Springer US, 2001, pp. 115–153.

[15] R. Burke, “Hybrid Recommender Systems: Survey and Experiments,” User Model. User-Adapt. Interact., vol. 12, no. 4, pp. 331–370, Nov. 2002.

[16] D. Jannach, M. Zanker, A. Felfernig, and G. Friedrich, Recommender Systems: An Introduction. New York: Cambridge University Press, 2010.

[17] Chennam, Krishna Keerthi, and M. Akka Lakshmi. "Cloud security in crypt database server using fine grained access control." International Journal of Electrical and Computer Engineering 6.3 (2016): 915.

[18] M. Montaner, B. Lopez, and J. L. de la Rosa, “A taxonomy of recommender agents on the Internet,” Artif. Intell. Rev., vol. 19, pp. 285–330, 2003.

[19] F. M. Santiago, F. A. López, A. Montejo-Ráez, and A. U. López, “GeOasis: A knowledge-based geo-referenced tourist assistant,” Expert Syst., vol. 39, no. 14, pp. 11737–11745, Oct. 2012.

[20] D. R. Fesenmaier, K. W. Wöber, and H. Werthner, Destination recommendation systems [electronic resource] : behaviourial foundations and applications / edited by Daniel R. Fesenmaier, Karl W. Wöber, Hannes Werthner. Wallingford, UK ; Cambridge, MA : CABI Pub., c2006., 2006.

[21] N. Leiper, “Tourist attraction systems,” Ann. Tour. Res., vol. 17, no. 3, pp. 367–384, 1990.

[22] K. L. Andereck and L. L. Caldwell, “The Influence of Tourists’ Characteristics on Ratings of Information Sources for an Attraction,” J. Travel Tour. Mark, vol. 2, no. 2–3, pp. 171–190, Feb. 1994.