

# Tourists Recommendation System using Decision tree algorithm Ms.M.ANITHA<sup>1</sup>, Mr. Y. NAGAMALLESWARA RAO<sup>2</sup>, Mr. B. Ravi<sup>3</sup>

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Abstract\_ Rapid advancements in Internet technology have resulted in everyone having their own mobile phone or laptop to access tourist information. The Tourist Recommended system is critical in assisting people in making decisions about their vacation. When someone visits a location, they will provide feedback after each visit, which will influence the decision-making of new users. To suggest the best hotel, all existing algorithms, such as collaborative or content filtering algorithms, use current user past experience data. If the current user has no previous experience data, these algorithms will fail. We use the C4.5 decision tree algorithm with the feature selection algorithm to solve the above problem. The suggested recommendation system is designed to make recommendations for all other sites worth visiting. This tourist recommendation system will be more useful in recommending destinations for visitors to new places. It prefers the ideal place by evaluating two factors: point of interest and ratings, and depending on the values of each attribute. C4.5, an ID3 extension, was created in [8]. C4.5 was chosen for this study because it attempted to address ID3's major flaws. [9] ID3 For classification, Quinlan's previous C4.5 method can be utilised. C4.5 Decision Tree is part of the Supervised Learning category.

#### **1.INTRODUCTION**

Every day, many people visit the ecommerce website to search required information such as well-known touristic locations around the world. People carries personal electronic devices such as mobile phone, laptops etc; are being able to gather information about their surroundings, which is used by the socalled tourist recommendation system to suggest touristic attractions, based on context factors such as location, etc. The statistics shows, Revenue of leading online travel Agencies worldwide 2018. In 2018 year, Booking was the leading travel agency with vield of a approximately 14.53 billion U.S. dollars. TripAdvisor have 37.7 million of visitors. (i.e April 2018 by monthly users) Booking.com has 20.1 millions of visitors. The usage of internet browser to



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read online reviews is improved in 2019 than the 2018. 51% of people were reading the reviews in a daily bases. 36% of people are always agreed with the online review. 18% are regularly viewing, 27% are occasionally views the online review. 18% are not liked to view. As per the review survey of 2019 done by bright local website, Online reviews were impacting on decision making of consumers or visitors as per the statistics of 2019, 91% of users are agree with the online reviews. The tourism industry is an extremely important sector on a global scale, East Europe the travel and tourism sector has a positive impact on economy contributing directly an estimated 782billon euro's to GDP in 2018. Europe is the global leader in international tourism with over 600 million tourists arriving in the region each year. Leading European countries in the travel and tourism in 2019 are Spain, Germany, UK. Switzerland, Austria. France, Portugal and Netherlands and Sweden. Tourist recommendation system will suggest the locations for visitors. Most of the earlier TRS have concentrated on approximate of selection the destination, activities (eg; restaurants, hotels) based on the user preference and interests. They are lacking sparseness adaptability, correctness. Perhaps the best test in building up a TRS that give customized proposals of traveler objections is to improve the vacationer decision making process. In the proposed system the tourist recommendation system will give the best location for the visitor. In order to achieve this, it requires a deep understanding of the tourist decisionmaking and develops novel models for their information search process. To develop this system initially we required a dataset of east Europe, feature selection Minimum methods. Redundancv Maximum Relevance (MRMR) algorithm [10] and decision tree of supervised machine learning for classification. C4.5 decision tree is for translation. The TRS has three proposed main innovations. Firstly, two feature selection used methods are to remove the unnecessary (both irrelevant and redundant) inputs into the system and to decrease the model complexity. Secondly, a decision tree C4.5 is utilized as a classifier to recognize the tourist destination selection process. Tourists can discover the travel information on sites, forums, websites of points of interest etc. However, information overflow can occur on the web as there is as yet an absence of spotlight on the utilization of recommender innovation in the travel industry field. During a trip, tourist should have the option to acquire visit data in a convenient way, whenever there are any changes in their planned tour. Recommendation system which provides tour information which is more useful for users, to succeed with the got information. There additionally is expanding interest for more data on local area attractions, for example, nearby food, shopping spots, spots of intrigue, etc during the visit. A tool to mine items and/or collect user's opinions to help users in their search process and suggests items related to their preferences [13], [14], [15].



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#### 2.LITERATURE SURVEY

2.1 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.

This article focuses on semantic network analysis as a means to investigate issues of usability of the Internet for travel information search. Usability of the Internet is viewed as the degree of match between mental models of information providers and information users, which are based on their understanding of information structure and information content on the Internet. The mismatch of mental models between the tourism marketers and the travelers contributed to the poor usability of the Internet as a information travel source. Bv investigating these two types of mental models using semantic network analysis, it can not only reveal their discrepancies, but also provide guidelines for effective information provision on the Internet. The authors focus on exploring the mental models of travel information though semantic network providers when they market their analysis destinations on the Internet, and provide a prelimi-nary result for the semantic network.

2.2 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. E-tourism is essentially the digitalization of the whole touristic industry and infrastructure. Some of the advantages of the reduction e-tourism are of successful seasonality. the more communication with the customers and the raise in reservations and sales in general. The use of the Internet has forever changed the structure and the principles of the touristic industry. The consumers-tourists are now capable of easily choosing their destination, of comparing prices and managing their financial exchanges. Information and communication technologies and Internet, if wisely used, can prove to be highly innovative strategic tools in the hands of the tourism entrepreneurs, that would help them upgrade the position of their facilities.

The aim of the research is to study the use of ICT by the Greek touristic industry and more precisely by non-coastal touristic units. The field of the research is the Municipal district of Loutraki Pellas. The research was realized in October 2012 and it was based on structured questionnaires that were completed by the means of personal interviews. The total of the 16 hotels located in Pozar participated in the research. The questionnaires are structured on five units of both open and closed-type questions.

2.3 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

Despite the explosive growth of electronic commerce and the rapidly



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increasing number of consumers who use interactive media (such as the World Wide Web) for prepurchase information search and online shopping, very little is known about how consumers make purchase decisions in such settings. A unique characteristic of online shopping environments is that they allow vendors to create retail interfaces with highly interactive features. One desirable form interactivity from a of consumer perspective is the implementation of sophisticated tools to assist shoppers in their purchase decisions by customizing the electronic shopping environment to their individual preferences. The availability of such tools, which we refer as *interactive* decision aids for to consumers, may lead to a transformation of the way in which shoppers search for product information and make purchase decisions. The primary objective of this paper is to investigate the nature of the effects that interactive decision aids may have on consumer decision making in online shopping environments.

#### **3.PROPOSED SYSTEM**

In this author is paper implementing C4.5 decision tree algorithm with MRMR features selection to recommend travel areas to tourist by using dataset from past tourist experiences. All existing algorithms such as collaborative or content filtering algorithms uses current user past experience data to recommend him new locations. These algorithms will not work if this current user has no past experiences data.

To overcome from above problem author is asking to use C4.5 decision tree algorithms which take experiences of previous users and then build a model and if new user enter his requirements then decision tree will predict best location based on his given input. Decision tree don't need new users past experience data.

To implement decision tree model we need to have dataset and this dataset sometime will have empty or garbage values and this values will put bad effect on decision tree model so we can remove such empty or garbage values by applying pre-process techniques.

Sometime to predict or build model no need to use all columns (attributes) values from dataset and this unnecessary attributes can be remove by apply features selection algorithms and here we are using MRMR features algorithms selection to remove unnecessarv attributes to reduce execution time of building model and to increase system accuracy.

### **3.1 METHODOLOY**

Now а dav's Machine learning algorithms are providing great results by reducing human interactions. Decision Tree Algorithm, which is a machine learning Algorithm is used to solve this classification problem. Decision tree is one type of a flow chart that was successfully applied to analyse the inputs and outputs. In our project we uses tourist data set which it is having 980 records of data with 12 different attributes that can be used for classification of the data by



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using feature selection methods and Decision Tree Algorithm. The inputs are given by the new sightseers to known the best location of the holiday tour. The input to the system is rating point of all the 11attributes which are given to the system based upon their preferences. The input contains rating points which are often used to classify the test data to the class to which it belongs to. The output after prediction it gives the final output as **4.RESULTS AND DISCUSSIONS** 

a location name. User can provide reviews to various places and also can view the reviews provided by the other users. User can provide reviews in rating points. The C4.5 Decision Tree were used for filter-based feature selection are generally calculated for one input variable at a time with the target variable. As such, they are referred to as univariant statistical measures.



Fig 4.1 In above screen click on 'Upload Tourist Dataset' button and upload dataset file

Run Preprocess & Features Selection Algorithm         1,0,93,18,2,29,062,08,2,42,3,19,2,79,1,82,2-42,Amsterdam_Heining           Run Prediction         1,0,93,18,2,29,0,62,0,82,42,3,19,2,79,1,82,2-42,Amsterdam_Heining           Run Prediction         1,0,93,18,2,29,0,62,0,82,42,3,19,2,79,1,82,2-42,Amsterdam_Heining           Run Prediction         1,0,93,18,2,29,0,62,0,82,42,3,19,2,79,1,82,2,42,Amsterdam_Jachthaven_jibur           Run Prediction         1,0,93,18,2,29,0,62,0,82,42,3,19,2,79,1,82,2,42,Amsterdam_Jachthaven_jibur           Solution         1,0,93,18,2,29,0,62,0,82,42,3,19,2,79,1,82,2,42,Amsterdam_Jachthaven_jibur           Run Prediction         1,0,93,18,0,29,0,70,44,1,54,318,2,63,1,31,2,5,Amsterdam_Bert Haanstra_Kad           Run Prediction         5,0,51,1,2,1,18,0,57,1,54,202,3,18,2,29,1,65,3,66,Amsterdam_Lengle           Features Selection Graph         9,1,12,1,76,1,04,042,0,2,1,43,112,2,79,1,43,125,4,Amsterdam_Nederlandse Rugby BondRugb	Ø	A De	cision Tree based Recommendation System for Tourists	- 🗇 🗙
Upload Tourist Dataset         D:/2019/Manoj/Tourist/python         userid,art_galleries,dance_clubs,juice_bars,restaurants,museums,resorts,parks_picnic_spots,beac           Run Preprocess & Features Selection Algorithm         1,0,93,1,82,23,0,62,0,82,42,3,192,79,1,82,2.42,Amsterdam_Heining           Run C4.5 Decision Tree         2,1.02,2.2,2.66,0.64,1.42,3,18,3.21,2.63,1.86,2.32,Amsterdam_Bert_Haanstra_Kad           Run Prediction         4,0,45,1.8,0.29,0.57,0.46,1.52,3.314,2.54,Amsterdam_Bert_Haanstra_Kad           Run Prediction         5,0.51,1.2,1.18,0.57,0.46,1.52,3.318,2.29,1.67,3.26,Amsterdam_Loetje_In_De_Ake           6,0.99,1.28,0.72,0.02,0.32,0.86,1.58,3.17,2.80,1.66,3.66,Amsterdam_The_Roya         8,0.74,1.40,22,0.41,0.82,1.5,3.17,2.81,1.54,2.88,Amsterdam_Kermis_Ubur           Features Selection Graph         9,1.12,1.76,1.04,0.64,0.82,2.1,4.3.18,2.79,1.14,3.18,2.79,1.41,254,Amsterdam_Mederlandse Rugby BondRugb		A Decision Tree based Re		
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Fig 4.2 In above screen all users past experience dataset loaded and total 12 attributes are there in the dataset. Now click on 'Run Preprocess & Feature Selection Algorithm' button to remove empty values and reduce attributes size.

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	A Decision Tree based Recommendation System for Tourists	
	Run Preprocess & Features Selection Algorithm       Selected number of features : [ True False False False True False Fals	
	Run Prediction Features Selection Graph	

Fig 4.3 In above screen after applying MRMR features size reduces to 3 and only those attributes will be used whose column is TRUE and FALSE column will be ignore. Now click on 'Generate C4.5 Decision Tree Model' to build model

A Decision Tree based	Recommendation System for Lourists	
Upload Tourist Dataset Dr.2019/Manoj/Tourist/ Run Preprocess & Features Selection Algorithm Run C4.5 Decision Tree Run Prediction Features Selection Graph	python       Selected number of features :   dance_clubs <= 0.94           resorts <= 2.23         restaurants <= 0.57             retaeters <= 1.81           retigious_institutions <= 2.57                   retigious_institutions <= 2.57	

Fig 4.4 In above screen we can see using IF and ELSE statement decision tree has generated model. If > it will choose some decision if < it will choose some other decision. Now click on 'Tourist Recommendation' button to upload test file with no location name and application will predict it

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		P V L C N	ideos cal Disk (C) ew Volume (D:) File name: test		_kard Id	2
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Fig 4.5 In above screen i am uploading test file now click open to get predicted or recommended location. In test file location name is not there application will give



Fig 4.6 In above graph x-axis contains total features and MRMR selected features and y-axis represents count of features and in above graph we can see after applying MRMR technique features size reduces to 3.



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#### **5.CONCLUSION**

In this paper, a decision tree based tourist recommendation system has been presented in attempt of solving the current challenge of the destination TRS. The data set has been decomposed into two sub data sets using relevant tourism domain knowledge. This was done to increase classification accuracy rate and to reduce the complexity of the decision tree. The optimal decision trees from NMIFS with the highest accuracy rate and simplicity (i.e. less number of leaf and tree size) have been constructed for destination choice. The decision rules from decision trees were extracted. For both data sets, it can be observed that NMIFS is the best method because it employs less features than MRMR. Finally, the experimental findings show that the proposed TRS is applicable. The proposed TRS meets the needs of tourists who are planning to visit or are already in Chiang Mai.

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