ISSN 2277-2685
IJESR/Jan. 2021/ Vol-11/Issue-1/1-6

Mr.K Anjineyulu ***et. al.,*** **/ International Journal of Engineering & Science Research**

A Context-Based Model for Mining Tourist Behavior Patterns

Mr.K Anjineyulu , Mr.A Srinivasan , Mr.K Ramanjulu

Assistant Professor [1,2,3]

Department of CSE,

Viswam Engineering College (VISM) Madanapalle-517325 Chittoor District, Andhra Pradesh, India

abstract

Research into providing tourists with a more tailored experience has become more important in the travel industry. In this paper, we consider the context and propose a contextually-aware method to the tourist: first, we analyse the context which influences the tourist behaviour patterns, select the main context factors, and construct the tourist behaviour pattern model; second, we calculate the interest degree of the tourist behaviour pattern and mine out the rules with high interest degree with the association rule algorithm; third, we can make some recommendations based on the rules with high interest degree. Finally, we conduct an experiment to demonstrate the viability and use of our approach.

Introduction

As the economy grows and people's living standards rise, more and more people are concerned about having a high-quality, tailored trip. More individualized forms of tourism, including FIT trips and self-guided vacations, have evolved in recent years. The standard travel service model is restricted in its ability to provide a wide variety of services and to cater to the specific requirements of individual travellers. The tourism service supply chain has struggled with how to discover the rules and characteristics of visitor behaviour via data mining. The pattern of tourist behaviour has been the subject of several studies. A new conceptual model for the tourism service supply chain was proposed by Qing based on the analysis of the characteristics of tourism services as well as the structural properties, constituent elements, and operation mechanism of the tourism service supply chain in the context of contemporary information technology [1]. Farmakis used Troodos, Cyprus, as a case study for his study of tourist motivation [2]; Martin and Witt proposed a tourism demand forecasting model to represent tourists' living expenses [3]; Smallman and Moore investigated the decision-making processes of vacationers [4]; and Kim et al. used a decision tree analysis technique to examine the purchasing habits of Japanese visitors [5]. These studies have focused only on the tourist from a psychological and behavioural science perspective, ignoring the many contextual factors that shape visitors' actions. Therefore, in this work, we investigate the context and provide a context-based analytical approach to the tourist in order to discover the connection between services in the journey and the context, as well as analyse the significant contexts that will affect the behaviour of the tourist. We propose a method based on network diagram that can clearly reflect the relationship of the contexts which influence the tourist behaviour in order to mine out rules with high interest degree with the association rule algorithm and do some recommendations to the tourist with better personalized traveling experience and services. By using this technique, we may exclude tourist behaviour patterns with a low interest degree and then mine the association rules of high-interest behaviour using the Apriorism algorithm. Finally, we conduct an experiment to demonstrate the viability and use of our approach.

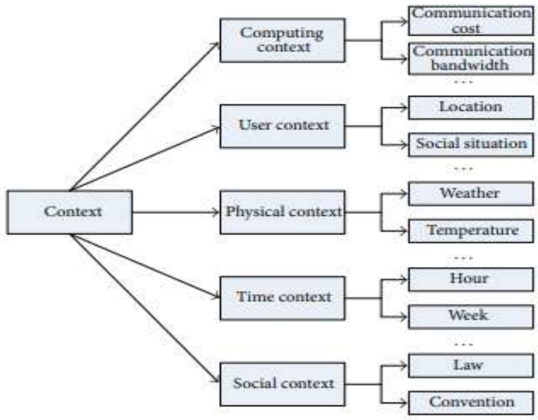

Figure 1: Context spectrum.

Related Works

Context.

Numerous scholars have attempted to provide various definitions of the context. Schilt et al. [6] defined context as the identification and movement of one's surroundings, including both people and things. Brown et al. proposed defining context as the signs around individuals or things, such as time, place, weather, and so on [7]. The study [8] proposes broadening the notion of context to include details about the people, places, and things around an item. As shown in Figure 1, the context has been variously defined. According to Snowdon and Grasso [9], the context is a multilevel structure that consists primarily of the individual layer, the project layer, the group layer, and the organization layer. Gu believed that the context would respond to the transformation based on the computers that serve as the centers for people. The computer (such as communication bandwidth), user (such as location), physical (such as weather, temperature), temporal (such as hour), social (such as law), and legal contexts were his categorizations [10]. In this work, we argue that visitors' actions are largely determined by their surroundings, with various situations producing markedly different results. The following factors may be considered: the user, the location, the time, the device, and the kind of service being provided.

Similarity Measure and Apriorism Procedure.

Association rules algorithms can be broken down into two categories: those whose primary focus is on enhancing the analytical efficiency of association rules, and those whose primary focus is on the application of association rule algorithms, dealing with value-type variables, and encouraging the expansion of associations from a single concept layer to multiple concept layers, all of which serve to reveal the objects' underlying structures. The Apriorism method was first proposed by Agrawal et al. [11], making it one of the traditional association rule algorithms. The algorithm consists mostly of two steps: (1) creating groupings of often occurring items, and (2) creating rules of connection between those sets. The method looks through the database, counts how many of each item there are, gathers up all the items that fulfil the minimal support (min sup), and then determines the most common 1-itemsets, which it labels as L1. To continue finding the frequent k-item sets, the method first utilizes L1 to discover the frequent 2-item sets L2, then L2 to find the frequent 2-item sets L3, and so on. To be considered robust in these common item sets, the confidence threshold of [12] must be met. Since its inception, the association rule algorithm has undergone extensive development and seen use in a wide variety of contexts. The Smart home [13] by Kang et al., and university teaching management [14] by Zhang et al., both made use of the association rule algorithm.

A Context-Aware Modelling and Mining Approach to Understanding Tourist Behaviour

Patterns of Tourist Behaviour and Their Environmental Influences.

A tourist fits the profile of a mobile consumer because of his or her constant need to be on the go. Very few academics are currently studying mobile consumers' habits. In order to mine client behaviours in a mobile service environment, Tseng and Lin introduced a technique called SMAP-Mine [15]. They reasoned that the service and location are the two most influential aspects. Ma et al. [16] built a context-aware model for mining mobile access patterns that takes temporal sequence into account. Using a four-way join between user, location, time, and service, Chen et al. [17] investigated the challenge of mining matching mobile access patterns. Therefore, in this research, we propose that mobile user, location, timing, and service type are all contextual elements that impact the behaviour pattern of mobile customers.

We also factor in the size of the customer's screen, how long their battery will last, and how much internet they have available. We predict that these features will have some kind of impact on the routines of mobile consumers. We do an experiment to demonstrate our point. In this setting, we tracked the service kinds, the trajectories of three consumers using various pieces of equipment, and the timing and nature of the services they used. We were able to get client movement trajectories (Figure 2) and a table containing details about service requests (Table 1). Figure 2 shows that consumer behaviour varies depending on the kind of mobile device being used. Using this illustration, we can deduce that when User u1 first used Device d1, his movement trajectory was l2 > l6 > l8 > l9, but after he switched to Device d2, his movement trajectory was l2 > l6 > l8 > l9.

Table 1: Customer service information table

Time instances	Users and devices					
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
T_1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
T_2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
T_3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
T_4	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]
T_5		[illegible]	[illegible]		[illegible]	
T_6		[illegible]				
T_7		[illegible]				

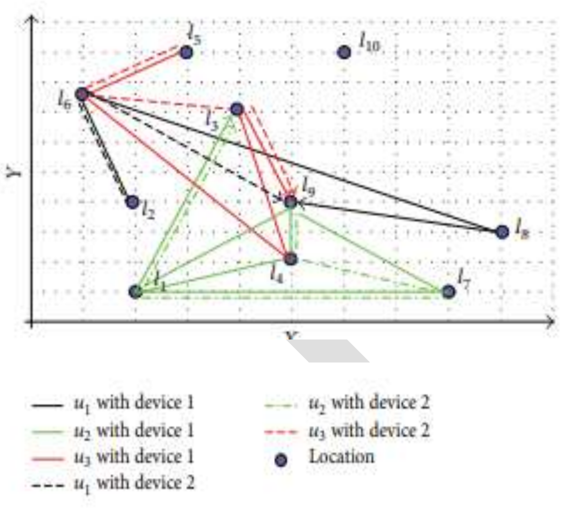

Figure 2: Movement trajectories of customers when they use different devices.

According to Table 1, the customer's service requests varied depending on the device he utilized or the time of day. For illustration, User u1 at Time t3 used Device d1 to request Service s3, and User u1 at Time t3 used Device d2 to request Service s4. Similarly, User u3 at Location l4 used Device d1 to request Service s2, and User u3 at Location l3 used Device d2 to request Service s2. These studies reveal that the mobile customer's mobility patterns, service preferences, and location-specific service demands all vary depending on the kind of device used. As a result, we consider the mobile device to be a contextual component that affects the behaviour pattern of mobile customers. The physical environment in which the customer resides (e.g., weather, temperature, humidity, etc.) and the social situations in which the customer is involved (e.g., manners, customs, and laws) are also context factors that influence the mobile customer behaviour pattern. We utilize the survey template to zero down on the most relevant environmental variables. We decide on a total of nine items to ask in this survey. The nine questions all have contextual elements that will have an effect on how tourists behave. We can learn about the kinds of

settings that matter via these inquiries.

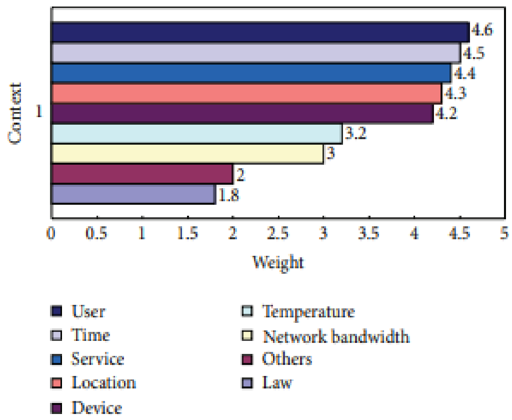

Figure 3: The results of the questionnaire.

tourist habits and routines most. There are a total of 102 visitors that fill out the survey. After distributing these surveys, we run them through SPSS for statistical analysis. We assign each possibility a weight (1–5), and then we use statistical methods to determine, on average, how the various contexts affect behaviour. Figure 3 displays the possible outcomes of our efforts. In this work, we focus on the following five context factors: traveller (user), technology (device), geography (place), time (clock), and service (offered).

Analyses and Tests

Case study/analysis.

To demonstrate the model's use, we use Hangzhou's West Lake as an example, showing how GPS and RFID may be used to tailor services to individual visitors based on their location, demographics, and interests at the lake. Therefore, we pull some of the data provided in Table 4 from the West Lake of Hangzhou Scenic Area Management Committee to better understand visitor habits. We utilize both the level of interest and the amount of coverage as measures of success for the suggested approach.

Table 4: Tourist behaviour information table

P	U_i	d_h	L_j	LC_m	T_m	T_s	S_u	T_r
p_1	u_1	d_1	l_1	1	t_{15}	8	s_4	6
p_2	u_1	d_1	l_1	1	t_{15}	8	s_3	2
p_3	u_1	d_1	l_1	1	t_{16}	11	s_2	3
p_4	u_1	d_3	l_1	1	t_{16}	11	s_3	4
p_5	u_1	d_1	l_8	4	t_{17}	21	s_8	17
p_6	u_1	d_3	l_3	4	t_{17}	4	s_3	3
p_7	u_1	d_1	l_5	11	t_{16}	35	s_4	30
p_8	u_2	d_1	l_4	2	t_{16}	9	s_5	9
p_9	u_3	d_3	l_3	2	t_{17}	9	s_5	9
p_{10}	u_2	d_1	l_8	2	t_{17}	2	s_8	1
p_{11}	u_2	d_3	l_3	2	t_{17}	28	s_5	15
p_{12}	u_5	d_2	l_2	8	t_{16}	38	s_4	31
p_{13}	u_8	d_1	l_8	6	t_{17}	5	s_8	5
p_{14}	u_3	d_3	l_5	6	t_{18}	12	s_5	8
p_{15}	u_8	d_1	l_8	6	t_{18}	12	s_4	4
p_{16}	u_3	d_1	l_5	6	t_{18}	18	s_3	13
p_{17}	u_3	d_2	l_8	6	t_{18}	18	s_8	5
p_{18}	u_8	d_2	l_8	10	t_{18}	32	s_4	30
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Based on the data in Table 4, we infer that P7, P12, and P18 are behaviours with a high interest degree because they include interesting places or interested services. In this research, we choose three user patterns and utilize them to create a five-layered network layout, gather the neighbouring layers, and compute the connection coefficients using Definition 7 (as shown in Figure 7). Then, we assign each user to a group and calculate the collection weight using Definition 8; we specify that edges with a weight of less than 0.2 will be removed, erasing edges such as d1l1, d2l1, t15s2, t15s4, l4t15, l5t17, t17s5, and t18s4 and patterns containing these edges, as depicted in Figures 8, 9, and 10.

conclusion

In this article, we took into account the whole range of contextual factors—including the tourist's chosen device, the time of day, the location, and the sorts of services available—that shape their behaviour. We then presented a way for mining visitor behaviour patterns using the network diagram, a procedure that began with the creation of the diagram itself. Then we executed association rule mining in the patterns and extracted the rules; finally, we conducted an experiment to demonstrate the viability and efficacy of our approach. After deleting the low-interest pattern and setting the low-interest degree th1 to 0.8 and the high-interest degree th2 to 1, we performed association mining using the Apriorism algorithm on the remaining patterns and obtained 39 rules, which we can use to make recommendations to tourists. The benefits of this approach over non-used outcomes are as follows: (1) it retains the rules of interest while removing the rules of no interest; (2) it generates many more rules of interest.

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