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The Application of Rough Sets to Spectacle Cost in Japan

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Abstract

The existing tourism need anticipating models in tourism are unable to receive useful information from a database with numeric and nonnumeric data. The present research discusses a new approach that applies the rough set theory to shape an anticipating model for supervising expenses in Japan. The rough set theory presents the classificatory analysis of ambiguous, uncertain, or incomplete knowledge (data) by containing the traditional set theory. Based on officially published tourist supervising information, decision principles are created to display the relationships among the independent variables and the dependent variable. Experimental results suggest that the anticipating model can systemize 91.1% of the testing cases, and that 82.5% of the systemized cases were the same as their real counterparts. There was no major difference between the real values and the anticipate values. The advantages of utilising decision principles induced by rough set to anticipate supervising expenses were also suggested.

Keywords: Tourism; Rough; Japan; Anticipate

Introduction

Many existing tourism articles have proposed the desires of travelers. Broadly speaking, the push and pull factors affect people to travel and affect their choice of a goal [1,2]. The push factors are the internal sociopsychological desires for example escape from a routine situation, relaxation, famous events, and social relationship. The pull factors connect to the appealing of a goal as apprehended by the travelers. The pull factors can be found in a tangible form, such as supervising points and recreational equipment's, or in an intangible form, such as the marketing image and the traveler's advantage expectations. Among other things, tourists meet a goal to meet historic places, scenic places, and museums [3]. Tourism expenses assist positively to the growth of local businesses in retailing, restaurants, accommodation, transportation, and entertainment [4]. Therefore, to find out tourists spending behavior better, it is useful to search tourism expense in a local market. In all points of measurements, Japan was the most well-known place in Asia during the 1993 to 2006. Worldwide visitors reached to Japan to observe different places of interest and to experience the significant international cuisine, world-class shopping centers, and unique East-meet-West culture. The booming tourism industry activated the growth of the retailing, lodging, restaurant, and arts and entertainment parts in Japan. As it is mentioned its income mostly from tourism, the local supervising tour industry depended heavily on tourism need for its existence. In this paper, supervising expense is explained as the "amount expense paid by visitors to connect local supervising tours in Japan." This contains expenses from locally shaped and overseas-formed tour groups but excludes the supervising expenses from single visitors who were not in a tour group (Table 1), based on data derived from A Statistical Review of Tourism published by the Japan Tourist Association [5], and shows the growth of the Japan tourism industry from 1993 to 2006. The amount supervising receipts and total visitor receipts showed a remarkable expansion in nominal terms during 1993-2006. When altered into real terms, using 1990 as the base year, the total supervising tax in 2006 was HK$1,425.55 million, displaying a fourfold increase compared with 1993 (HK$434.84 million).Because of its limited geographical site (slightly more than 1,000 km^2), Japans supervising points are all easily got [5]. No matter whether tourists meet Ocean Park, Stanley Market, or Victoria Peak, they will experience a special mixture of different. For example, there is the coexistence of the high-tech Mass Transit Railway (subway), half-century-old trams, manually operated sampans, and new expensive yachts, while bicycles carrying fresh pork travel through some of the most expensive residential and commercial buildings in the world. This mixture of new Western technologies and centuries-old Oriental civilization makes Japan a best site in the world and this uniqueness many visitors to look at the historical characteristics of this former British society. Naturally, supervising contains expenses on local hotels, transportation services, restaurants, entertainment venues, cultural Centers, and retailing outlets. Thus, supervising highly contributes to the increasing of the Japan economy. Past researches have displayed that supervising expenses is connected with major demographic variables. To verify, Hsieh, OLeary, and Morrison [6] revealed that supervising packages for Japan travelers are highly connected with age group, income, education, gender, marital status, life cycle, and occupation. In the same way, income, age, date, occupation, and tax revenues were determined to have an influence on Americans supervising expenses [7,8]. In their research, Cai, Hong, and Morrison [4] suggested that supervising expenses by Americans is associated with age, marriage, occupation, education, race, and region. Also, Uysal, Fesenmaier, and OLeary [9] wrote that length of a stay impacts a visitors spending behavior, containing supervising. At the end, it is possible that a nonnumeric dummy variable for a specific event such as the Gulf War in 1990 [10] can affect travelers expenses on supervising (Table 1).

Despite tourism supervising major contribution to an economy, the number of previous researches on formal modeling of supervising expenses and its determinants appears to be very limited. This is particularly true in the Japan context. Earlier research articles rarely, if ever, tried to make a formal anticipating model to show the interactions of the supervising expenses and its determining variables. A formal anticipating model that explicitly explains the relationship between

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Year	Tourism industry	Sightseeing arrival	Total visitors receipt	Percent of total visitors
1993	2.665,011	272,66	9,456.11	2.41
1994	3.032,112	244.44	11,323.33	2,33
1995	3.363,112	222,98	13.118.21	2.25
1996	4,083,641	480.21	16,233.93	2.82
1997	4,917,055	641.2	22,737.14	2.75
1998	6,147,112	755.36	31,476.16	2.4
1999	5,984,501	672.49	35,842.86	1.88
2000	6,490,850	820.42	36,966.86	2.12
2001	6,685,413	895.92	36,110.56	2.32
2002	8,090,324	1,020.67	43,668.76	2.15
2003	8,997,700	1,554.56	57,207.43	2.62
2004	9,391,156	1,705.07	61,411.87	2.86
2005	10, 918,994	2,128.65	71,839.61	2.91
2006	11,702,735	2,682.14	81,452.38	3.21

Table 1: A profile of the Japan tourism industry.

supervising expenses and its associated factors would surely help tourism policy makers and practitioners to find out tourist spending behavior more clearly and would consequently help them to plan for future progression more accurately.

At present, multivariate backslide (econometric) techniques, time-series models, and multivariate gravity models conquest connection modeling in tourism [11,12]. A multivariate backslide technique utilises a multivariate mathematical action to determine the numerical connection between a group of independent variables and a dependent variable (these variables are usually some economic factors in tourism) [13,14]. In the same way, a gravity model highlights the amount of relationship between two geographic spots utilising a multivariate mathematical function [15]. In another way, a time-series model utilises just historical information about a variable to form a mathematical action that represents the previous performance of that variable [16,17]. A natural use of these interactive models is to anticipate the future values of a specific tourism behavior based on the established models. That is, the interactive models are applied, based on previous action, to anticipate or project the future action. The success of progressing an interactive model based entirely on the availability of historical information.

The traditional tourism interactive modeling techniques have received a certain level of success [12]. Although, in reality, most of the tourism databases are not completely numeric. To discuss, a typical lodging property profile contains the property type, equipment type, and service type, which are all nonnumeric variables. This is also right for supervising expenses databases. Unfortunately, the existing formal interactive models in tourism have been completely occupied by the aforementioned numeric database models. Most of the past formal interactive modeling researches in tourism management have failed to receive the interaction of a group of information with at least one nonnumeric variable (hereafter called mixed information).

From the viewpoint of the lack of a formal modeling strategy for handling mixed information in tourism, the present paper suggest to incorporate the rough set theory (borrowing from the field of artificial intelligence in computer science) into mixed information interactive modeling in the light of supervising expenses in Japan. Instead of utilizing mathematical actions, a rough set approach can generalize the information of a data-base and display this generalized finding in a set of decision rules. Past researches in medical and financial fields have stated the successful applicability of the rough set theory in mixed information classification and interactive modeling [18,19].

The next part of the present paper critically compares and contrasts the traditional tourism anticipating models and the decision-rule—based anticipating model. Describing the fundamental rules of a rough set model, containing the basic concept, Information Table (IT), approximation accuracy, data reduction, and decision principles induction then follows it. An example will be given to discuss the application of a rough set model to a hotel reservation IT. On the basis of the rough set theory, and utilizing published tourism information from the Japan Tourist Association, an IT is progressed for supervising expenses in the Japan field. The automatic principle induction way is then displayed. Next, an empirical part shows the induced principles and illustrates the usage of these principles as an anticipating model. The results fore-cast by the rough set model are then compared with the real values. At the end, a conclusion part summarizes this research, signifies the importance of findings, outlines some management implications, and bids future research offerings.

A Comparison of Rough Set and Other Tourism Forecasting Models

Generally, tourism predicting approaches fall into two major categories, namely, qualitative and quantitative approaches. A qualitative forecasting approach, such as an expert opinion technique [11] or a desk reviewing method [20], emphasizes the qualitative insight, intuition, and no verifiable knowledge of a specific tourism phenomenon. The likelihood of possible events in the future is then forecast based on these qualitative aspects. While a qualitative approach could be useful when few informants are available or when time pressures do not allow formal research, the cost of such usefulness could be huge as a result of credibility lost. Results from qualitative research in tourism are "artistic in nature" and cannot be used for generalization, teaching, or scheduling [21]. Hence, a formal scientific model that accurately represents the relationship between sightseeing and its associated demographic factors would surely help tourism policy makers and practitioners to understand sightseeing behavior more clearly.

Quantitative tourism forecasting models apply mathematical functions to estimate the quantitative relationships between some phenomena in numeric tourism data. On the basis of their past performance, these models are then used to project the future values. Traditional quantitative tourism forecasting studies have largely concentrated on time-series models, multivariate regression analyses, and gravity models.

Making no assumption about other factors, time-series forecasting models use historical data about a variable to form a mathematical function that represents the past performance of the variable. Based on the developed function, future values are then predicted [22]. Due to their simplicity, time-series models can achieve reasonably good forecasting results [14,16]. However, a fundamental limitation of time-series forecasting models is their inability to predict changes that are not only based on past data about the sole variable.

In multivariate regression analyses, the relationship between a dependent variable and a set of independent variables is identified and represented in a multivariate mathematical function. This function is then used to predict future values of the dependent variable. Multivariate regression models are commonly known as econometric models, because economic factors such as income, travelling cost, living cost, and exchange rates are used to build the regression model [13,14,23-25]. Despite their relatively high explanatory power and prediction accuracy, multivariate regression models have limitations as well. The most important limitations include the existence of multi collinearity among the independent variables and difficulties in data collection. Moreover, traditional econometric tourism forecasting models implicitly assume that economic data are stationary, but Witt and Witt [12] pointed out that it is unknown whether these models can cope with recent developments concerning the dynamic structure in econometric theory.

On the basis of Newton's Gravitation Law, tourism researchers developed gravity models to measure the degree of interaction between two geographic areas [15]. In its simplest form, the interaction strength changes directly with population numbers in these two areas and inversely with the geographical distance separating these areas. Strictly speaking, gravity models are a special class of econometric models. However, gravity models are only applicable under very restrictive limitations [12]. For example, gravity models can only forecast the number of tourist arrivals but no other important variables such as occupancy rate and expenditure. Also, gravity models assume a homogeneous person per trip type. Consequently, trips made by tourists with different income levels are beyond the explanatory scope of a typical gravity model A decision-rule–based forecasting model prevails over the other formal forecasting models in terms of simplicity and practicability. Generally speaking, a decision rule is in the form of "IF_condition(s)_THEN_decision(s)." If the condition(s) in the "IF" part matches the given fact(s), the intention(s) in the "THEN" section will be accomplished. Unlike mathematical functions or statistical models in traditional tourism forecasting analyses, decision rules induced from a set of raw data can obtain and display both numeric and nonnumeric variables. In addition, a decision rule always consists of a single and relatively independent piece of information. Unlike the other mathematical-oriented models, the modular nature of decision rules makes it easy for industrial managers and researchers to add new decision rules or to alter existing intention rules without affecting the overall system. As well as, it is relatively easier and more meaningful to explain a process by citing the particular rule(s) used in reaching the conclusion as by citing a complicated mathematical function [26].

To summarize, mathematical functions and statistical models are the key tools used in traditional, formal tourism forecasting research. However, the capabilities of traditional forecasting models have long been known and widely exploited. Unfortunately, this situation has almost reached its peak [26,27]. That is, only marginal improvements in forecasting are likely to be achieved, even with large additional development efforts on these traditional methods. Consequently, revolutionary or evolutionary new forecasting techniques are needed to enhance, if not to revolutionize, tourism forecasting capacity. The incorporation of the rough set theory into sightseeing forecasting is surely the most promising path.

An Overview of the Rough Set Theory

Basic concepts

The theory of rough set was originated by Pawlak in the early 1980s [28]. The methodology is concerned with the classificatory analysis of imprecise, uncertain, or incomplete knowledge (data) by incorporating the classical set theory. Knowledge classification is the partitioning of the universal set "U" into a number of small distinguishable categories called elementary sets. A rough set is a collection of objects that generally cannot be classified precisely to the subset of interest. In the rough set approach, any vague information is substituted by precise lower and upper approximations. These approximations are the most vital concepts in dealing with uncertainties [29]. The lower approximation is a description of the domain objects that are known with certainty to belong to a subset of interest, whereas the upper approximation is a description of the objects that possibly belong to the subset. It follows that any subset falling through its lower and upper approximations is called a rough set. In Figure 1, Px represents the lower approximation (also known as the positive region) of a concept or subset of interest. Px, on the other hand, represents the upper approximation. The difference between Px and Px is known as the boundary region of the concept of interest x. In this boundary region, every object cannot be clearly classified into the concept x or –x (i.e., not x) using knowledge P. The union of elementary sets outside set x is known as the set x negative region.

Information table

The primary application of the rough set model is dependency analysis and pattern recognition in an IT. Similar to previous studies [18,26,30], in this research, an IT (sometimes called a decision table), represents input data gathered from any domain. An example of a simplified hotel reservation IT is shown in Table 2, with Room Rate Type (RR_TYPE) being the dependent variable and other attributes being the independent variables. Rows of an IT, such as the guests from Robert hoff to Tim Gamble, are the objects of an IT. Objects are characterized by features expressed as pairs (attribute, value). For example, "RESERVATION=Airline" and "RM_TYPE=NK" are some of the features of the object "Robert hoff" in Table 2. Each attribute has a number of possible values. The list of possible values of an attribute is called its domain.

Accuracy of set approximation

The accuracy of the set approximation on a concept is determined by the size of the boundary region. If there is no boundary region, the approximation is precise, and it would always be possible to distinguish a concept based on available information. Although smaller elementary sets will minimize the size of a boundary region and will yield more precise and detailed approximation, these elementary sets also contain fewer objects and represent weak patterns. As the boundary gets larger, the approximation becomes less accurate. More objects are contained in major elementary sets, and this produces a potent data template. It is the essential target of knowledge discovery to identify this data pattern. Hence, controlling the details or "roughness" of set approximation will depend on the goals of the data analysis (Figure 1).

Information reduction

It is possible that some attributes in the IT are irrelevant or have no

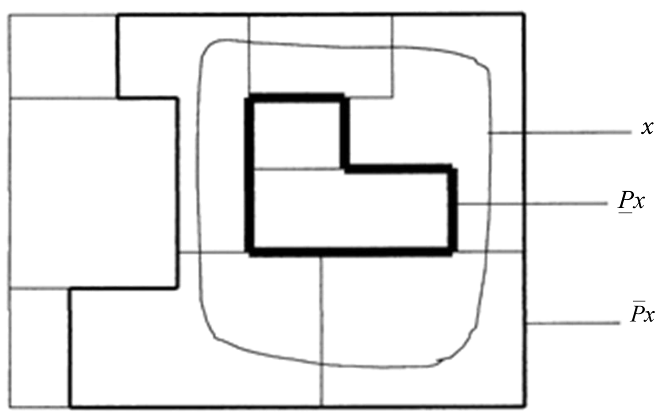

Figure 1: Approximate classification of set *X*.

RR_TYPE	PAYMENT	ARR_MONTH	NIGHTS	G_TYPE P_VISITS		RM_TYPE	RESERVATION	GUEST
Non Rack	Visa	September	2	8	SIT	NK	Airline	Robert hoff
Rack	AE	October	1	3	FIT	NK	G_Direct	Monica freman
Rack	AE	September	3	3	BUSINESS	SQ	Airline	May Navas
Non Rack	D_Debit	January	3	4	GIT	NK	G_Direct	Yanicaadams
Non Rack	D_Debit	March	1	3	SIT	PS	Airline	Rob Stives
Non Rack	D_Debit	October	2	9	GIT	SQ	Tr_Agent	Petty Hales
Rack	Visa	October	2	1	BUSINESS	PS	G_Direct	Susan Louis
Non Rack	Visa	February	6	5	SIT	NK	CRS	Novak Rodrigueze
Non Rack	AE	January	2	6	FIT	PS	G_Direct	TommDropller
Non Rack	D_Debit	February	4	3	GIT	NK	CRS	Janet Wrigh
Rack	Cash	September	2	1	FIT	SQ	Airline	Derick Bond
Rack	AE	October	2	2	FIT	NK	Airline	Tim Gamble

Note: RESERVATION: Reservation Source; RM_TYPE: Room Type; G_TYPE: Guest Type; P_VISITS: Number of Previous visits; NIGHTS: Number of Nights Stayed; ARR_MONTH: Guest Arrival Month; PAYMENT: Payment Method; RR_TYPE: Room Rates type; G_Direct: Guest Direct; CRS: Computerized Reservation System; Tr_Agent: Travel Agents; SIT: Special Interest Group; FIT: Foreign Independent Traveler; GIT: Group Inclusive Tour; Rack: Full Rate; Non Rack: Discounted Rate.

Table 2: A sample hotel reservation information table.

RR_TYPE	ARR_MONTH	P_VISITS
Non Rack	September OR October	≥4
Non Rack	January OR February OR March	
Rack	September OR October	<4

Note: P_VISITS: Number of Previous Visits; ARR_MONTH: Guest Arrival Month; RR_TYPE: Room Rates Type.

Table 3: A reduced table for hotel reservation information system.

additional effect on discerning dependency on the decision attribute. When all redundant attributes have been removed without losing any essential information, the remaining subset that contains only urgent attributes is denominated a reduct. It is possible for one IT to have more than one reduct. In that case, either one of them can be used to represent the information in the IT. In the example of Hotel Reservation IT, the reducts are

1. ARR_MONTH, P_VISIT, RR_TYPE
2. ARR_MONTH, RR_TYPE

Discovering redacts and variable independencies is considered to have primary importance in the rough set approach in relationship analysis [19]. In addition, the core of an IT is defined as the intersection of all reducts. Hence, a core is the collection of the most significant variables in an IT. In other words, one cannot eliminate a core variable without changing the dependencies of an IT. However, the core set could be empty. Since there are only two reducts, the core of Table 2 is therefore ARR_MONTH, RR_TYPE. The next subsection presents an example of how to extract the most essential information, in terms of decision rules, from Table 2.

Decision-rules induction

Decision rules are obtained from nonredundant attributes contained in the chosen reduct. The rules can identify data patterns hidden in an IT that link the value of specific attributes (independent attributes) with an outcome (decision attribute). Table 3 shows the same information as Table 2 in terms of classification ability.

The procedure of capturing decision rules from a set of raw data is known as induction [31]. Therefore, the following induced decision rules are extracted from Table 3:

1. IF[ARR MONTH=(Sept OR Oct)] AND [P VISITS> 4] THEN RR TYPE=NonR

2. IF [ARR_MONTH=(Jan OR Feb OR Mar)] THEN RR_TYPE=Non Rack

3. IF [ARR_MONTH=(Sept OR Oct)] AND [P_VISITS < 4] THEN RR_RATE=R

The above three rules (or Table 3) summarize the IT in Table 2, which states that the demand for hotel rooms is basically influenced by seasonal fluctuation. In general, a discount rate (i.e., non-rack rate) will be given to all guest types during January, February, or March (low season in the Japan hotel market) to attract more business. However, during peak season (i.e., September and October), a rack rate (i.e., maximum rate) is normally charged to guests who have stayed at a hotel fewer than four times in the past 12 months. On the other hand, to reward loyal customers, guests who have stayed at the hotel four or more times in the past 12 months will be charged at the non-rack rate, regardless of the arriving month. A tour group and a special interest group are two typical examples that fall into this last category. These two groups are more likely to generate regular and repeat business to the hotel throughout the year. Based on the above rules, hoteliers can identify the key factors that determine the rate types to be charged for hotel rooms. Among the eight in-dependent variables (GUEST, RESERVATION, RM_TYPE, G_TYPE, P_VISITS, NIGHTS, ARR_MONTH, PAYMENT) in Table 2, only two variables (P_VISITS, ARR_MONTH) can significantly influence the decision variable (RR_TYPE).

Method

In this research, a secondary source of data was used to build sightseeing IT. All data were extracted and derived from A Statistical Review of Tourism published annually by the Japan Tourist Association during the period 1983 to 1996 [5].

In this study, additional factors such as the recommended length of stay, the percentage of first-time visitors, and the percentage of visitors who had joined local tours were included. All factors included in this study were relevant to sightseeing expenditure [5].

In this article, sightseeing expenditure was selected as the dependent (decision) variable. The independent variables comprised the following attributes:

1. Region—original market source
2. Age 30—percentage of visitors with age ≥30
3. Male and Female—percentage of male and female visitors
4. Married people—percentage of married visitors.

Career—percentage of visitors with superior white collargarbage

1. Hotel Stay—percentage of visitors who had stayed in commercial hotels
2. LOS—average length of stay by visitors in number of days
3. RECLOS—recommended length of stay by tourists in number of days
4. First Visit—percentage of first-time visitors
5. Tour—percentage of visitors who had joined local tours
6. Return—percentage of visitors who opted for returning to Japan on their future trips.

It is necessary to mention that some of the above variables, such as RECLOS, could become superfluous in the induced IT. On the basis of sightseeing expenditure as a percentage of total tourists spending, an equal percentile approach was used to transform sightseeing expenditure data into two major categories, namely, High and Low. These two categories equate with the equivalence classes of the decision variable in an IT. The transformation process allows tourism decision makers, especially those involved in sight-seeing facilities, to identify the market segments of customers based on their sightseeing expenditure. Among the 82 available data entries, 65 (78% of the observations) were randomly chosen to build the rules induction IT, and the remaining 17 entries were used to build the testing IT (Table 4).

Empirical Findings

A computer program was execution using DLogic version 1.5 for the regulation infusion IT. DLogic is a generic computer program developed on the basis of the rough set theory. This software was chosen because of its low cost and its capability to category small data sets. Output generated from the computer software included six decision rules, presented in Table 4. In other words, the following decision rules (extracted from Table 4) describe the information of the 65 entries in the rules induction IT.

1. IF[Region=(Oceania OR Asia)] AND[61≤Age 30≤64] THEN Sightseeing Expenditure=H
2. IF [Region=(Oceania OR N Asia)] AND [Age 30 < 61 OR Age 35 > 64] AND [37 ≤ Local Tour ≤ 59] THEN Sightseeing Expenditure=H
3. IF [Region=Europe] AND [37 ≤ Local Tour ≤ 59] THEN Sightseeing Expenditure=H
4. IF [Region=(SE Asia OR Indonesia)] AND [Age 30 < 61 OR Age 30 > 64] AND [37 ≤ Local Tour ≤ 59] THEN Sightseeing Expenditure=H
5. IF [Region=(America OR China)] THEN Sightseeing Expenditure=L
6. IF [Region=(SE Asia OR Indonesia)] AND [Local Tour < 37 OR Local Tour > 65]

THEN Sightseeing Expenditure=L.

In Table 4, the core set of the reduced sightseeing IT consists of Region, Sightseeing Expenditure, and the superfluous variables include Male, Married, Career, Hotel Stay, LOS, RECLOS, First Visit, Return. These superfluous variables appear to be insignificant in determining sightseeing expenditure. The comprehension of the induced decision rules is straightforward. To illustrate, Rule 5 states that expenditure on sightseeing by visitors from America or China was relatively low. The contributing reasons could be that there were not enough attractive sightseeing spots for these groups of visitors, or that these visitors were more interested in expenditure on shopping or dining. In 1996, 28% of the visitors in Japan were from China and America [5]. This large market segment means that the Japan tourism policy makers should develop more diverse sightseeing attractions and a richer cultural heritage plan to motivate American and Chinese visitors to increase their expenditure on sightseeing. Although an in-depth examination of the induced decision rules could be interesting and useful, the primary objective of this study is to investigate the feasibility of decision-rules induction from a set of hybrid sightseeing data. A detailed qualitative analysis of the induced rules is thus beyond the discussion scope of this article [32-35].

Forecasting

Accuracy

Based on the six induced decision rules, data in the testing IT were then used to forecast sightseeing expenditure. To determine the forecasting accuracy, actual sightseeing expenditure values were compared with their corresponding forecast counterparts. Experimental results are presented in Table 5.

In Table 5, among the 17 entries of testing data, 16 were successfully classified with the induced decision rules, representing

Sightseeing Expenditure	Local Tour	Age35	Region
High	≥ 37 and ≤ 59	≥ 61 AND ≤ 64	Oceania OR North Asia
High		< 61 OR > 64	Oceania OR North Asia
High	≥ 37 and ≤ 59		Europe
High	≥ 37 and ≤ 59	< 61 OR > 64	Southeast Asia OR Indonesia
Low			America OR China
Low	< 37 OR > 65		Southeast Asia OR Indonesia

Table 4: A reduced sightseeing information system.

17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	Case
L	H	H	H	L	L	H	H	L	L	L	H	H	H	L	L	H	Actual
H	H	H	H	L	L	H	H	H	L	L	ND	H	H	L	L	H	Forecast

Note: H: High; L: Low; ND: No Decision.

Table 5: Experimental results.

91.1% of the testing cases. Among the 16 successfully classified cases, 14 were accurately forecast (i.e., fore-cast values and actual values were identical). This represented an 82.5% forecasting accuracy. For the classified samples in Table 5, a nonparametric Wilcoxon Matched-Pairs Signed-Ranks Test for two related samples was performed to compare the means of the forecast data and actual data. Numeric values of 1 and 2 (High=2 and Low=1) was.

A Diagram for Successfully Classified Cases

SPSS output showed for a two-tailed test, Z=-1.212 and p=0,146 at α=0.05, indicating that the mean of the actual group equals the mean of the forecast group. In other words, the six induced decision rules can forecast sightseeing expenditures with no significant difference between the forecast and actual values. It shows the relationship between the actual and forecast values for the classified cases.

Conclusions and Implications

This article has discussed the importance of sightseeing expenditure in the Japan economy and the necessity of developing a formal forecasting model for sightseeing expenditure. Also, the concept of rough sets was explained, and its rule induction capability as applied to tourism research was analyzed. Following the theoretical foundation, an IT for sightseeing was built. Using the induced decision rules, a sightseeing expenditure forecasting model for Japan was developed. The accuracy of the forecasting model was tested with published data. Empirical findings indicated that the induced rules can forecast 91.1% of the test data and that there was no significant difference between the actual values and the forecast values. This indicates the rough set theory's applicability in the context of formal tourism forecasting.

As for practical implications, there are several advantages offered by the forecast model in sightseeing expenditures using decision rules induced by a rough set. First, it is relatively easier for the practitioners and policy makers to understand a peculiar tourism phenomenon from a set intention rules rather than from intricate mathematical function. Also, knowing the mixed demographic patterns that are associated with a specific market segment for sight-seeing expenditures, tourism decision makers can carry out more accurate planning activities. More important, practitioners and researchers may then confidently apply the rough set approach as a forecasting technique by modeling the relationship of mixed tourism data. Due to the fundamental nature of mathematical functions, nonnumeric tourism data are simply beyond the analytical scope of the existing tourism forecasting models. As mentioned earlier, it is unrealistic to assume that all tourism data are numeric. Therefore, tourism professionals must refocus their attentions to new techniques for developing formal forecasting models to capture useful knowledge about sightseeing expenditure and other tourism-related factors. Currently, the Japan tourism industry is experiencing a downturn in terms of tourist arrivals, because Japan is over expensive, overcrowded, and over polluted [20]. The bird-flu crisis and the regional financial turmoil have significantly increased this downturn effect since October 1997. Therefore, it is hoped that the research outcomes of this study will benefit the tourism industry in Japan by contributing to improve planning.

This research is an initial attempt to devise a forecasting model for hybrid data in the sightseeing expenditure domain. With a relatively small data set, the empirical results of this study, although useful in terms of forecasting accuracy for the chosen data, cannot be generalized to the sightseeing industry at large. In other words, it is unknown whether the induced decision rules represent sightseeing behavior in general. Due to data unavailability, another limitation of this study is the decision rules' inability to explain seasonal sight-seeing expenditure behavior. A future study could collect seasonal sightseeing expenditure data and induce decision rules based on these seasonal data. Interesting results could be obtained by comparing and contrasting the annually based decision rules with the seasonally based decision rules.

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