Comparing the Relationship of Tourist Attraction by Using Association Rule

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Abstract

One of the many effects of the coronavirus outbreak is the suspension of businesses in the tourism sector. Currently, the Indonesian government is starting to loosen quarantine, however the virus is still around. Therefore, all sector needs to consider various strategy options so that they can rise again and survive in the new normal times. In this research, market basket analysis, which is commonly used in the retail sector, is adopted in the tourism sector. The method used is the Association Rule but using survey data, whereas usually used transaction data. Respondent data then divided into two datasets based on the respondent age to see differences in decision making on choosing tourist attractions. The two datasets are the age group under 40 and the age group above 40. The results indicate that the Association Rule with data collected from the questionnaire can be made. Also, show the differences in decision patterns between the two groups observed. Respondents under the age of 40 tend to choose relatively new tourist spots, while respondents above 40 tend to choose the 'classic' Bali. From the rules formed, the age group under 40 produces 15 rules, while the age group above 40 produces seven rules.

Keywords
Association Rule, Tourism, Market basket analysis, Association rule

1. Introduction
The tourism sector is one of the sectors most affected by the spread of the coronavirus. This deadly virus is spreading rapidly, crippling many businesses. The modern era, with international flights that easily connect countries with countries accelerate the spread of this virus to the corners of the world. As a result, many airlines are forced to be grounded, and hotels are forced to close, tourist attractions are empty. Of course, this will have a tremendous impact on the economy of a country, especially countries that rely on the tourism sector, such as Indonesia. Quarantine is also enforced in Indonesia for almost three months. Although the quarantine easing already started, still this dangerous virus exists around the environment. So that the people of Indonesia must go to work, school, or shopping with the awareness that this virus is still around, this condition is called the new normal, when life today is not the same as before the outbreak. The economy must move again, align with staying alert to the coronavirus outbreak. The new normal situation is also faced by the tourism sector. Thus, it requires considering various strategies in order to rise and survive in this situation.

The tourism sector must focus on customers to be able to get back up and survive because the tourism sector is potentially increasing the economy in one region (Truong, 2018). Therefore, both businesses and administrators of tourist attractions must attach great importance to customer satisfaction, with understanding consumer needs and consumer behavior (Chadee & Mattsson, 1996; Owusu-Frimpong et al., 2013). Another sector that is also very dependent on customer satisfaction in the retail sector. Predicting the behavior of prospective tourists is significant for tourism stakeholders (Calder et al., 2016). Therefore, the retail sector already develops many techniques to be able to continue to improve its services, one of which is by conducting market basket analysis. Hence, we believe that the techniques commonly used in the retail business can be adopted in the tourism sector.

Market Basket Analysis is often used to study customer buying patterns. The intention is to look for patterns of relationships between the purchases of an item with other items. Its uses are various, including determining the location of the placement of goods, services, and promotions (Sharda et al., 2018). Usually, market basket analysis uses the association rule method by utilizing transaction data.

In the retail world, product bundling is common. To the knowledge of the researcher, research related to tourist destination packages has never been done. This study tries to make product bundling in the form of tourist destinations that are in accordance with consumer expectations. This will be done by using the association rule approach. Furthermore, it is hoped that this research will show differences in the pattern of tourist visits in different generations.

Association rule will be used in this study to see the pattern of tourist attraction selection. The analysis is to predict the decision-making of prospective tourists. The decision-making is critical to be analyzed by tourism managers because by predicting the decision-making, the tourism managers can prepare what prospective tourist needs (Karl, 2018).

Nevertheless, dissimilar from the data commonly used in retail businesses, which is transaction data. In this study, the data used are gathered from questionnaires. This method is used because most tourists visit tourist attractions, have two options, using travel agents, or arrange their own trips. If the traveler uses a travel agent, trips are usually offered in the form of travel packages. As a result, the choice of tourist attractions depends on the package offered by the agent, not really the desire of the consumer. Besides, transaction data will be in the form of packages, not stand-alone items. If a traveler arranges his own trip, it becomes more challenging to get the data.

This research will use tourist attractions in Bali. Bali was chosen because, in Indonesia, Bali is the most visited tourist destination. So, the tourism sector in Bali is a critical sector for Indonesia (Chong, 2020). Furthermore, the coronavirus outbreak has hit tourism in Bali hard. Bali needs to rise quickly in the new normal times by understanding consumers more. One way to understand consumers is to use market basket analysis. The technique, which is commonly used in retail businesses, will be adopted in the tourism sector using data taken from questionnaires.

1.1 Objectives
The purpose of this study is to see differences in decision making on choosing tourist attractions among two set group by using market basket analysis, which commonly use in retail then we try to adopt the concept by use questionnaire.

2. Literature Review and Methods
The data mining activities can usually be divided into three major categories: estimation, association, and clustering. In this research we use association technique. The aim of association rule mining is to find in big datasets an interesting relationship between variables or items. It is typically known as market basket analysis due to its successful implementation in retail business issues. (Sharda et al., 2018). The market basket analysis shows which element classes occur more frequently during exchanges. These relationships may be used to help, promote, resell, or place items on the menu or in the shop to drive revenue. If further analysis is conducted, Market Basket Analysis may allow companies to identify valuable goods that are distinguishable in the market, and that could cause harm or costly to businesses if they are not present. (Ünvan, 2020).

An approach for analyzing market baskets using association rules was initially proposed by Agrawal et al. (1993). Each activity includes items purchased by a customer during a visit. They have an efficient technique which generates all necessary rules for sales number in the database. There were originally two main criteria for such a technique: Support and Confidence. According to Chauhan (2019), the standard popularity of a product is Support. The Support for item A in mathematical terms is the proportion of transactions involving A to the total transaction number. Thus, Support ranging 0-1 with the closer to 1 the better. Same as Confidence, which is the probability that consumers purchased both A and B. The number of transactions concerning A and B is divided by the number of transactions concerning B. And Lift is increased in the sale of A when the company sells B.

Association Rule-based algorithms are characterized as a two-step approach; the first step is Frequent Itemset creation, which finds all frequent item-sets as per the specified minimum Support. The second step is the Generation rule, which lists all of the Association Rules from regular products. Evaluate the Support and Confidence of all rules. Prune rules fail to achieve minimum support and minimum confidence levels.

From the literature that can be studied, generally, the data used in Association Rule is transaction data. Like the research conducted by Setiabudi et al. (2011). The market basket analysis approach was implemented in minimarkets X. A search for the Apriority algorithm frequent articles to obtain articles that frequently appear in the repository and the pair articles in one single transaction. The frequently selected itemsets will include a pair of items that exceed the minimum Support. After decoding, frequent items exceeding minimum support yield association rules. The results of the test show that the application can gain information over what types of goods consumers often buy simultaneously, according to the Association rules of the hybrid dimensions. Setiabudi et al. (2011) used transaction data in their research.

The data used in this study was collected using a questionnaire. To better understand the consumers, the data is divided into two, namely respondents under 40 years old and respondents above 40 years old. This grouping was done because it is suspected there is a difference in pattern between the older generation and millennial generation for choosing tourist attraction (Ryan & Mo, 2001) (Tsiotsou & Vasioti, 2006). In the questionnaire, respondents were asked to choose a maximum of 7 out of 25 attractions in Bali. Restrictions of 7 attractions were taken based on observations of average packages commonly offered by travel agents. This restriction is done to force respondents to choose maximum of 7 locations that they really wanted to visit. There are 90 more attractions in Bali, the selection of 25 attractions is based on the number of reviews from Google.

Google can provide information about tourist attractions in an area. Users can review these tourist attractions, therefore, the more tourist attractions reviewed, the more famous these attractions are. Based on the number of reviews, tourist attractions in Bali are sorted from the most reviewed to the least reviewed. Then 25 is chosen. This method is used so that respondents are not confused due to too many choices, and we assumed that respondents know about these attractions because the place is well known. The tourist attractions in this research are Tanah Lot, Garuda Wisnu Kencana Cultural Park, Mandala Wisata Wenara Wana, Tegallalang Rice Terrace, Pura Luhur Uluwatu, Pura Ulun Danu Beratan Bedugul, Tegenungan Waterfall, Monumen Bajra Sandhi, Pura Tirta Empul, Double Six Beach, BALI ZOO, Pasar Badung, Waterbom Bali, Tirta Gangga, Kebun Raya Bali, Bali Bird Park, Bali Safari & Marine Park, Pura Besakih, Campuhan Ridge Walk, Bali Swing, Jatiluwih Rice Terraces, Ubud Palace, Taman Ayun Temple, Dream Museum Zone (DMZ), Pantai Pandawa.

Data from 307 respondents were collected and then divided into two based on age. There are 187 data for age groups under 40 years and 120 data for age groups above 40 years. Both datasets are then processed using RapidMiner. RapidMiner is software for conducting data mining without coding. In data processing, RapidMiner uses square operators, and users only need to connect the operators.

3. Results and Discussion

For this study, RapidMiner operators to process association rules were formed. RapidMiner is a well-known computer program for data mining. One of the advantages from RapidMiner is that the user does not need to code anything. RapidMiner uses square operators. Users only need to connect between the right operators without coding. It should be designed for no coding, but RapidMiner has a function to use Python scripts if needed. In figure 2, the Retrieve operator is used to retrieve data that has been previously imported. One Retrieve operator to retrieve the age group under 40 datasets, another Retrieve operator to retrieve the age group dataset above 40.

The next set of operators is the same for both datasets. “The Numerical to Binomial operator” converts “numerical data” into “binomial data.” Because the “FP-Growth processing” requires “binomial data types.” FP-Growth operator is used to forming frequent itemset, and then the Create Association Rule operator is used to form Rule based on predetermined parameters.

In this study, the minimum Support used is 0.2 because Support with a value above 0.2 is quite high (Zhang & Zhang, 2003), and the minimum Confidence used is 0.5. The 'find min number of itemsets' parameter is unchecked so that dynamic support values are off; thus, a fixed number of minimum Support value is used (FP-Growth - RapidMiner Documentation, 2020).

Table 1. Frequent Itemset for Age Group Under 40 Dataset

Size	Support	Item 1	Item 2
1	0.540	Pantai Pandawa	
1	0.529	Tanah Lot	
1	0.487	Ubud Palace	
1	0.481	Garuda Wisnu Kencana Cultural Park	
1	0.396	Waterbom Bali	
1	0.364	Double Six Beach	
1	0.358	Bali Safari & Marine Park	
1	0.294	Pura Luhur Uluwatu	
1	0.289	BALI ZOO	
1	0.209	Bali Bird Park	
2	0.316	Pantai Pandawa	Tanah Lot
2	0.278	Pantai Pandawa	Ubud Palace
2	0.262	Pantai Pandawa	Garuda Wisnu Kencana
2	0.235	Pantai Pandawa	Waterbom Bali
2	0.246	Pantai Pandawa	Double Six Beach
2	0.203	Pantai Pandawa	Pura Luhur Uluwatu
2	0.305	Tanah Lot	Ubud Palace
2	0.299	Tanah Lot	Garuda Wisnu Kencana
2	0.203	Tanah Lot	Waterbom Bali
2	0.251	Ubud Palace	Garuda Wisnu Kencana

Table 1 shows the results of the Frequent itemset with the specified minimum Support. The highest support value of the dataset is 0.540, Pandawa Beach. FP-Growth also showed results of up to 2 itemsets with the Support value above 0.2 was quite a lot. Overall, the results in Table 1 show the order of tourist attractions for the age group under 40. Pandawa Beach is a tourist attraction that often appears and often appears together with other tourist objects.

Table 2. Association Rule for Age Group Under 40

Premises	Conclusion	Support	Confidence	LaPlace	Gain	p-s	Lift	Conviction
Pura Luhur Uluwatu	Pantai Pandawa	0.203	0.691	0.930	-0.385	0.044	1.279	1.488
Double Six Beach	Pantai Pandawa	0.246	0.676	0.914	-0.481	0.050	1.252	1.421
Ubud Palace	Tanah Lot	0.305	0.626	0.878	-0.668	0.047	1.183	1.260
Garuda Wisnu Kencana Cultural Park	Tanah Lot	0.299	0.622	0.877	-0.663	0.045	1.175	1.246
Tanah Lot	Pantai Pandawa	0.316	0.596	0.860	-0.743	0.030	1.103	1.138
Waterbom Bali	Pantai Pandawa	0.235	0.595	0.885	-0.556	0.022	1.101	1.134
Pantai Pandawa	Tanah Lot	0.316	0.584	0.854	-0.765	0.030	1.103	1.132
Tanah Lot	Ubud Palace	0.305	0.576	0.853	-0.754	0.047	1.183	1.210
Ubud Palace	Pantai Pandawa	0.278	0.571	0.860	-0.695	0.015	1.058	1.073
Tanah Lot	Garuda Wisnu	0.299	0.566	0.850	-0.759	0.045	1.175	1.194
Garuda Wisnu Kencana Cultural Park	Pantai Pandawa	0.262	0.544	0.852	-0.701	0.002	1.008	1.010
Garuda Wisnu Kencana Cultural Park	Ubud Palace	0.251	0.522	0.845	-0.711	0.017	1.073	1.074
Ubud Palace	Garuda Wisnu	0.251	0.516	0.842	-0.722	0.017	1.073	1.073
Pantai Pandawa	Ubud Palace	0.278	0.515	0.830	-0.802	0.015	1.058	1.058
Waterbom Bali	Tanah Lot	0.203	0.514	0.862	-0.588	-0.006	0.970	0.967

The results of the Association Rule can be seen in Table 2 and sorted by Confidence value. The highest Confidence value is Pura Luhur Uluwatu with Pandawa Beach, which is 0.691, and the lowest is Waterbom Bali with Tanah Lot, which is 0.514. Lift values are all greater than one, which shows an interesting relationship, as well as Conviction greater than 1. Next are the results for the age group dataset above 40 years. Table 3 shows the results of the Frequent itemset that appears with a minimum Support value of 0.2.

Table 3. Frequent Itemset for Age Group Above 40

Size	Support	Item 1	Item 2
1	0.525	Tanah Lot	
1	0.417	Garuda Wisnu Kencana	
1	0.4	Pantai Pandawa	
1	0.375	Ubud Palace	
1	0.308	Pura Besakih	
1	0.267	Pura Ulun Danu Beratan	
1	0.258	Bali Safari & Marine Park	
1	0.25	Bali Bird Park	
1	0.25	Pasar Badung	
1	0.242	Kebun Raya Bali	
1	0.233	Pura Luhur Uluwatu	
1	0.208	BALI ZOO	
2	0.283	Tanah Lot	Garuda Wisnu Kencana Cultural Park
2	0.242	Tanah Lot	Pantai Pandawa
2	0.233	Tanah Lot	Ubud Palace
2	0.225	Tanah Lot	Pura Besakih
2	0.208	Garuda Wisnu Kencana	Pantai Pandawa

For the age group above 40, Tanah Lot is a tourist attraction with the highest Support value of 0.525. In contrast to the results of the age group under 40, where Pandawa Beach is the highest. FP-Growth showed results up to 2 itemsets with Support value above 0.2 was a lot but not as much as the age group under 40.

Table 4. Association Rule for Age Group Above 40

Premises	Conclusion	Support	Confidenc	LaPlace	Gain	p-s	Lift	Convictior
Pura Besakih	Tanah Lot	0.225	0.730	0.936	-0.392	0.063	1.390	1.758
Garuda Wisnu Kencana	Tanah Lot	0.283	0.680	0.906	-0.550	0.065	1.295	1.484
Ubud Palace	Tanah Lot	0.233	0.622	0.897	-0.517	0.036	1.185	1.257
Pantai Pandawa	Tanah Lot	0.242	0.604	0.887	-0.558	0.032	1.151	1.200
Tanah Lot	Garuda Wisnu	0.283	0.540	0.842	-0.767	0.065	1.295	1.267
Pantai Pandawa	Garuda Wisnu	0.208	0.521	0.863	-0.592	0.042	1.250	1.217
Garuda Wisnu Kencana	Pantai Pandawa	0.208	0.500	0.853	-0.625	0.042	1.250	1.200

Table 4 shows the results of the formed Rule Association. Unlike the previous group, in the age group above 40, only seven rules are formed. However, the highest Confidence value can reach 0.730, Besakih Temple with Tanah Lot, with a Support value of 0.225. While the lowest Confidence value is 0.5 with a Support of 0.208, the Garuda Wisnu Kencana Cultural Park with Pandawa Beach. Lift values are all greater than one which shows an interesting relationship, as well as Conviction greater than 1. Garuda Wisnu Kencana Cultural Park is paired twice with other tourist objects. While in the age group below 40, Pandawa Beach is the most frequently appearing along with other tourist objects. Next is Tanah Lot, which often appears along with other tourist attractions. Comparing table 2 with table 3, the pair of tourist objects that appear in both tables are Ubud Palace and Tanah Lot, Pandawa Beach and Tanah Lot, Tanah Lot with Garuda Wisnu Kencana, Garuda Wisnu Kencana with Pandawa Beach.

One of the uses of the results of the Association Rule is to determine the placement of goods, for example, in supermarkets. In this research, another approach is needed. By using a Google Map, travel time from one place to another can be known easily. So in Table 5 and Table 6, the travel time attribute from Premises to Conclusion is added.

Table 5. Traveling Time for Rules in Age Group Under 40

Premises	Conclusion	Support	Confidence	Traveling time
Garuda Wisnu Kencana	Pantai Pandawa	0.262	0.544	00:19:00
Waterbom Bali	Pantai Pandawa	0.235	0.595	00:35:00
Double Six Beach	Pantai Pandawa	0.246	0.676	00:44:00
Waterbom Bali	Tanah Lot	0.203	0.514	00:48:00
Ubud Palace	Tanah Lot	0.305	0.626	01:02:00
Tanah Lot	Ubud Palace	0.305	0.576	01:02:00
Tanah Lot	Garuda Wisnu	0.299	0.566	01:04:00
Garuda Wisnu Kencana	Tanah Lot	0.299	0.622	01:05:00
Ubud Palace	Garuda Wisnu	0.251	0.516	01:12:00
Garuda Wisnu Kencana	Ubud Palace	0.251	0.522	01:15:00
Pura Luhur Uluwatu	Pantai Pandawa	0.203	0.691	01:19:00
Pantai Pandawa	Tanah Lot	0.316	0.584	01:19:00
Ubud Palace	Pantai Pandawa	0.278	0.571	01:20:00
Tanah Lot	Pantai Pandawa	0.316	0.596	01:23:00
Pantai Pandawa	Ubud Palace	0.278	0.515	01:23:00

Table 6. Traveling Time for Rules in Age Group Above 40

Premises	Conclusion	Support	Confidence	Traveling time
Pantai Pandawa	Garuda Wisnu	0.208	0.521	00:19:00
Garuda Wisnu Kencana	Pantai Pandawa	0.208	0.500	00:19:00
Ubud Palace	Tanah Lot	0.233	0.622	01:02:00
Tanah Lot	Garuda Wisnu	0.283	0.540	01:03:00
Garuda Wisnu Kencana	Tanah Lot	0.283	0.680	01:05:00
Pantai Pandawa	Tanah Lot	0.242	0.604	01:19:00
Pura Besakih	Tanah Lot	0.225	0.730	02:07:00

Traveling time is also considered by travelers when moving from one tourist place to another (Marques et al., 2019) so travel time needs to be considered in this study and decision making. The longest travel time is from Besakih Temple to Tanah Lot, which is 2 hours 7 minutes. The shortest travel time is from Pandawa Beach to the Garuda Wisnu Kencana Cultural Park and vice versa. It should be remembered that this data was not asked when the respondents filled out the questionnaire but was plotted when the results of the association's processing appeared. So that the location that is said to appear together may have quite an actual distance.

4. Conclusion

Indonesia begins to loosen quarantine, which had lasted for almost three months. However, economic conditions have not yet fully recovered, and coronaviruses are still around. The tourism sector slowly begins to reopen, but the environmental conditions of the tourism sector are not as they used to be before the outbreak. Considering how vital this sector is to the country's economy, various efforts are needed to raise it, one of which is to focus on the customers. The tourism sector has to understand consumer needs better.

For this reason, market basket analysis, which commonly used in retail, is adopted to the tourism sector. Usually, in the retail sector, the data used is transaction data. Nevertheless, in this study, the data used came from the questionnaire data obtained from the survey. This method of data retrieval is done because it is difficult to get transaction data for the case of tourism.

One of the objectives of this study is to demonstrate the use of questionnaires to conduct association rules. The results show that by using a questionnaire, association rules can be executed and produce some interesting rules. The implication of this finding is that stakeholders in the tourism sector can make decisions using the association rule without using transaction data.

Also, this study tries to reveal differences in the patterns of choice of tourist attractions based on age. The results show there are differences in patterns between the age groups below 40 or what is commonly called millennial group, and the age groups above 40. Millennial tend to choose tourist attractions that are new to Bali. While the age groups above 40 tend to choose the classic tourist attractions in Bali. This difference may also occur because millennial have better access to information, so they have knowledge about new tourist sites than those whose age is above 40 years. Although there are differences, these two groups seem to both like Tanah Lot and Garuda Wisnu Kencana Cultural Park. Both places often appear together with other tourist attractions. This equation might emerge because indeed the two locations are favorite locations in Bali as indicated by the large number of reviewers on Google for both locations.

This study produced 15 rules for the age group below 40 and 7 rules for the age group above 40 years. Based on these rules, tourism businesses can arrange tour packages that are more suitable for their consumers based on age, considering the value of Support, Confidence, and travelling time from one place to another place. For example, Garuda Wisnu Kencana, Waterbom Bali, and Double Six Beach can be used as one package of holiday in Bali because of Support, Confidence, and travel time that is short between those locations. Local governments can facilitate access to tourist attractions that often appear together. Also, providing direct transportation between sites that are safe and comfortable, providing a price to enter several tourist attractions.

Although the use of questionnaires in this study gave quite encouraging results, caution was needed. By using a questionnaire, the desires of consumers can be revealed. However, the choice of tourist attractions by consumers when filling out the questionnaire will not consider the required budget, although the problem is tried to be approached by limiting choices. Therefore, future research can be done by trying to include the budget into the respondents' considerations; this can be done using simulations. Further study also can be applied to a larger population of study to cater to a variety of perspectives tourists. This research highlights the implications of the tourist perspective in decision-making. It provided essential findings from the tourist’s point of view relating to the tourism destination. Originality and value from the research, there is still a small number of studies that predicting decision-making from the tourist through data mining methods.

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