Analysis of Vessel Movements using Association Rules

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Keywords: Vessel Movements, Association Rules, VISITS

Abstract: Currently, ship traffic and the situation of sea waters are essential for several countries, including Indonesia as an archipelago. The automatic Identification System of ITS (VISITS) provides data containing a variety of information about vessel movements and traffic characteristics in Java sea waters. We use data mining techniques to identify and determine ships' movement patterns in the Java sea, especially the Lombok Strait. The objects of research are ships around the Lombok Strait because it is one with hefty ship traffic. Based on the analysis results, we obtain information that the dominant types of ships passing in the Lombok Strait are cargo ships with medium vessel speed and relatively spread out the course over ground, as many as 25% of ships heading to the South. Furthermore, using the a priori algorithm association rules method, 14 rules are obtained for a maximum of 3 items and 26 rules for a maximum of 4 items. The rules with the highest lift score state that if the ship's coordinates are at Latitude = 7 and Longitude = 116, and type = Cargo ship, then the course over ground is about 180° - 225° or the vessel is heading South.

1 INTRODUCTION

Indonesia is a country with a big sea area called an archipelago. Indonesia has the potential to develop the existing marine. Apart from abundant marine resources, Indonesian seas are also a route for world trade. As much as 90% of world trade routes are transported by sea, 40% of this trade passes through Indonesia. Indonesia has an opportunity to become a World Maritime Axis Country by improving an integrated marine transportation system. Traditionally, the process of tracking vessels at sea is using radar. However, with the development of technology, currently, there is a satellite-based Automatic Identification System (AIS) to monitor the activities and movements of ships passing in sea waters.

AIS data provides much information, including ship identity, passage time, latitude-longitude, type, speed, course over ground, etc. Predicting the status of vessel motion, patterns, and ship anomaly status can use that type of data (Gustisatya, 2017). The result is essential to maintain the security of interactions between ships and ship traffic in sea waters.

Several data mining approaches have been applied to AIS data to analyze ship movements used the Association rules and Markov model to inform the motion patterns of ships in Chinese waters (Deng, et al., 2014). The Markov model became the solution for the continuous transaction. In 2011, Mascaro detected anomalous motion of ships passing through Sydney waters using the Bayesian Network method (Mascaro, et al., 2013). Furthermore, the visualization and interaction of anomalous status on ships in Sweden using the combined Gaussian Mixture Model and Kernel Density Estimation and Clustering based on the ship's trajectory (Riveiro and Falkman, 2014). Zhu F applies Agrawal's association rule in mining ship trajectory patterns (Agrawal, et al., 1993).

In this study, we analyse the vessel movements using the association rules method based on the frequency. This work aims to determine an appropriate pattern of vessel motions. The result sustains and simplify to control, monitor, and predict the vessel's activities. The paper is structured as follows. In the first section, the background and descriptions of several studies were appropriate. The second section explained the analytical methods used in the study, followed by the research methodology covering the data sources and pre-processing. In the third section, data analysis consists of ship data characteristics and ship motion patterns using association rules. The last section is the conclusion of the research.

Santoso, N., Wibowo, W. and Azizah, N.
Analysis of Vessel Movements using Association Rules.
DOI: 10.5220/0010797800003317
In *Proceedings of the 2nd International Conference on Science, Technology, and Environment (ICoSTE 2020) - Green Technology and Science to Face a New Century*, pages 125-130
ISBN: 978-989-758-545-6

2 RESEARCH METHODS

Data mining is the exploration and analysis of a set of data to find essential patterns and rules (Margaret, 2003). There are several data mining techniques, including classification, clustering, and association rules, where each technique has a different function. The following section will describe the theory of the association rules.

2.1 Association Rules

Association rules are techniques of data mining to find patterns of the combination of an item. The function of the association rule is to find shared value items that often appear together in a database. Several references mention association rule with market basket analysis based on a priori algorithm which has the principle "if an itemset is frequent appears, then all subsets of the itemset are also frequent appear". This principle refers to the nature of the support measure, which means that the support of an item set is less than its data subsets support.

The importance of a rule is determined according to two parameters: support (the percentage of the item combination) and confidence (the strength of the relationship between items). Association analysis has defined a process for finding all associative rules that meet the minimum requirements for support score and minimum requirements for confidence score [8]. The function to determine the support value of one item as follows:

$$support(A) = \frac{\{number\ of\ item\ A\}}{\{\ number\ of\ all\ item\}} \quad (1)$$

Equation (1) shows that item A's support is determined by dividing the number of item A that occurs with all items. Meanwhile, the support of items A and B (two items) is calculated by equation (2) as follows:

$$support(A,B) = \frac{\{number\ of\ item\ A\ and\ B\}}{\{-number\ of\ all\ item\}} = P(A \cup B) \quad (2)$$

The next step after finding all high-frequency patterns is searching the rule which meets the minimum of confidence. The confidence score is a measure of the rule's accuracy. The highest confidence, the most substantial relationship between items in the association rules. Formulas to calculate the confidence score of two items are as follows:

$$confidence(A \to B) = \frac{support(A \cup B)}{support(A)} = \frac{P(A \cup B)}{P(A)} \quad (3)$$

$$Lift(A \to B) = \frac{confidence\ (A \to B)}{support(B)} = \frac{P(A \cup B)}{P(A)P(B)} \quad (4)$$

Furthermore, a priori algorithm also uses score lift as a parameter. Lift is a ratio number that shows how many times it is possible to find an attribute that occurs with other attributes compared to all occurrences of the whole attribute. The value obtained from the lift score shows the strength or failure of the resulting rules, also supported by the value of the support and confidence generated (Melita, et al., 2013). The function to determine the lift score is written in equation (Riveiro and Falkman, 2011).

2.2 Dataset

The study uses a limited area and period of AIS dataset. The selected AIS data from 1st October 2018 to 31st December 2018, which distributed from latitude S 7,14° to S 8,55° and longitude E 115,29° to E 116,03° as visualized in Figure 1. There are over ten thousand records in the raw dataset. Therefore, we do pre-process covering data cleaning and data transforming.

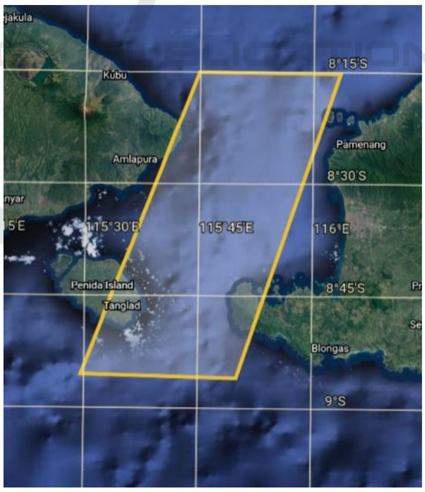


Figure 1. Coordinate point selected area

2.3 Methodology

In the data cleaning process, first, we delete data without MMSI, position, time, course over ground, speed and ship type. Second, fill the ship type with the same MMSI. Third, removing multiple data (exact time and location) and finally removing unused attributes in the analysis. Table 1 present the attributes used in this study.

Table 1. Attributes of research

Attribute	Definition	Data type
MSI	*Maritime Mobile Service Identify*	Integer
Latitude	Latitude ship position	Numeric
Longitude	Longitude ship position	Numeric
Speed	Speed of ship (km/hr)	Numeric
Course overground	course over ground of ship	Numeric
Type	Type of ship (cargo, passenger, thanker)	Text

The last pre-processing is data transformation. We perform a transformation on the attributes of the ship speed and course over the ground. Based on the AIS dynamic information standard (Deng, et al., 2014), we categorized the speeds into five, which are presented in Table 2. The "Exceptions" speed category is anomalous data. Usually, the recorded data is due to recording errors. In this study, we did not find a ship with more than 99 km/hr speed. Additionally, based on information from the data and the weather in the water area, we define the course over ground attribute into eight categories. The interval for each category is 45° as written in Table 3. After pre-processing the data, about 60% of the data remains for further analysis.

Table 2. Discrete of speed

Range of speed (km/hr)	Category
0 – 3	Slow
3 – 14	Medium
14 – 23	High
23 – 99	Very high
over 99	Exception

Table 3. Discrete of course over ground

Interval	Category
360° - 45°	North
45° - 90°	North East
90° - 135°	East
135° - 180°	South East
180° - 225°	South
Interval	**Category**
225° - 270°	South West
270° - 315°	West
315° - 360°	North West

3 RESULTS AND DISCUSSION

In this section, the results describe into two subsections, namely descriptive statistics and association rules analysis.

3.1 Statistics

The characteristics of the AIS data analyzed include speed, type, and the distribution of the ship's course over ground from the clean data obtained in the pre-processing. The results of the analysis are presented in Figure 3.

Based on Figure 3, ships with medium speed and cargo ships have the most significant proportion. We know that the area used in this study is around the Lombok Strait, which is a busy trade route with a high level of ship traffic density. So that the speed "Medium" - "Low" is the recommended condition to avoid ship accidents.

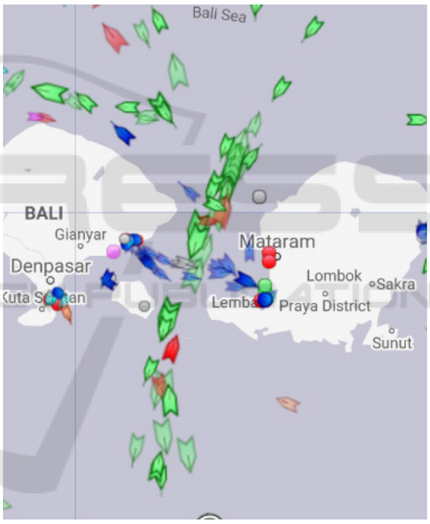
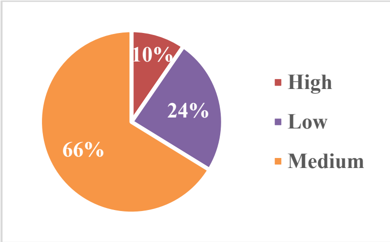
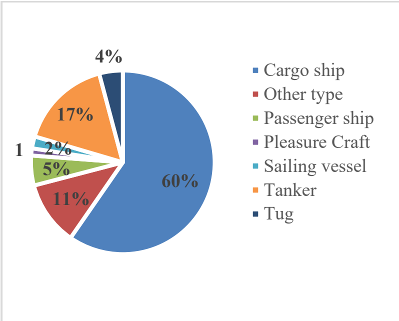


Figure 2. Traffic in the Lombok Strait

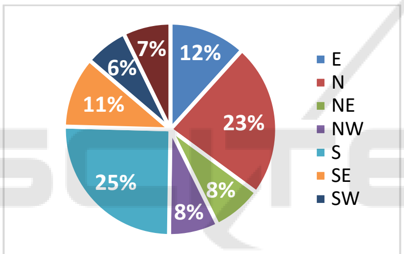
Besides, the distribution of the course over the ship's ground shows relatively balanced data. There are 25% of ships toward the South, 23% of ships move towards the North, and the rest spread in other directions according to their destination. Visually, the marine traffic around the Lombok Strait can be seen in Figure 2. In this figure, the green-coloured ships, namely the type of cargo, dominate the water traffic in the Lombok Strait. Either across the island of Lombok - Bali, as well as to other islands.



(a)



(b)



(c)

Figure 3. statistics of data based on (a) speed, (b) type, and (c) course over ground

3.2 Association Rules Analysis

This study analyses vessel movement data using association rules that use a priori algorithm method based on the lift value. Lift is a ratio number that shows how many times it is possible to find an attribute with other attributes. Rules formation is obtained based on item appearance. In this study, the items in question are the course attributes over the ground, speed and type of ship. We set two schemes to compare the performance. The result of each scheme is described as follows.

3.2.1 Scheme 1

Scheme 1 builds rules with a priori algorithm with the provisions of the parameter max length = 3, support = 0.1 and confidence = 0.8. The results are 14 rules. Here are five rules based on the highest lift.

Table 4. The highest five rules of scheme 1

lhs	*RHS*	*support*	*confidence*	*lift*	*count*
{Latitude=7, Longitude=116}	{Course=S}	0.1296	0.8275	3.281	331
{Latitude=7, Course=S}	{Longitude=116}	0.1296	0.9143	2.937	331
{Longitude=116, Course=S}	{Type=Cargo ship}	0.1495	0.8967	1.504	382
{Latitude=7, Longitude=116}	{Type=Cargo ship}	0.1366	0.8725	1.464	349
{Latitude=7, Course=S	{Type=Cargo ship}	0.1225	0.8646	1.450	313

Based on Table 4, it can be explained in the first rule that if the ship's coordinate point is at Latitude = 7 and Longitude = 116, then the course over ground is South or the ship is from the South direction. These rules have a lift score of 3.281 with 82.75% confidence, 0.1296 support, and the number of activities with the same item is 331 ships. At the value of lift 1.45, the rules are if Latitude = 7 and Course = South, then the type of ship is cargo. The level of confidence for these rules is 86.46%, followed by support at 0.1225. Visually, the distribution of parameter values in all rules can be seen in Figure 4.

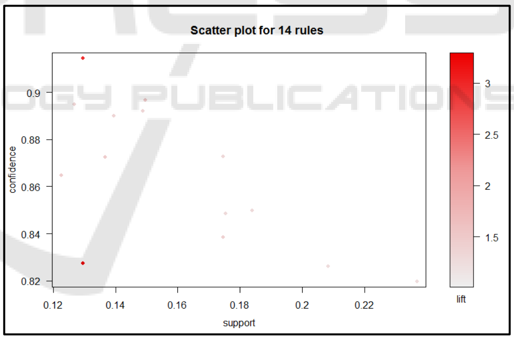


Figure 4. Scatter plot of the parameter by scheme 1

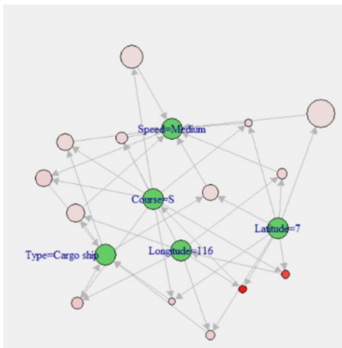


Figure 5. Rules pattern by scheme 1

Based on Figure 4, the rules with high confidence have a high lift value (the colour is getting brighter), but the support value is relatively small. Conversely, rules with a higher support value lower the lift value (the colour fades), with a confidence value ranging from 80% to 90%. The visualization of patterns between items that often appear is shown in Figure 5, which can be explained that items Speed = Medium and Type = Cargo Ship are items that become result (RHS) indicated by the direction of the arrow leading to the item. Meanwhile, the items Course=South, Latitude=7, and Longitude=116 are required (lhs) indicated by the direction of the arrow that comes out of the item. The green colour shows the main item, the red colour shows the high lift value, and the large circle size shows a high confidence value.

3.2.2 Scheme 2

Scheme 2 builds rules with a priori algorithm with the provisions of the parameter max length = 4, support = 0.1 and confidence = 0.8. The results are 26 rules. Here are five rules based on the highest lift.

Table 5. The highest five rules of scheme 2

lhs	*rhs*	*support*	*confidence*	*lift*	*count*
{Latitude=7, Longitude=116, Type=Cargo ship}	{Course=S}	0.1194	0.8739	3.465	305
{Latitude=7, Longitude=116, Speed=Medium}	{Course=S}	0.1170	0.8398	3.330	299
{Latitude=7, Longitude=116}	{Course=S}	0.1296	0.8275	3.281	331
{Latitude=7, Course=S, Type=Cargo ship}	{Longitude=116}	0.1194	0.9744	3.130	305
{Latitude=7, Course=S, Speed=Medium}	{Longitude=116}	0.1170	0.9228	2.964	299

Based on Table 5, it can be explained in the first rule that if the ship's coordinate point is at Latitude = 7 and Longitude = 116, the type = cargo ship, then the course over ground is South. These rules have a lift score of 3.465 with 87.39% confidence, 0.1194 support, and the number of activities with the same item is 305 ships. Visually, the distribution of parameter values in all rules can be seen in Figure 6. Based on Figure 6, the lift value is inversely proportional to support. Rules with a high lift value (bright red colour) followed by a support value of 0.12 - 0.13.

On the contrary, the higher the support value, the smaller the lift value (pink colour). Likewise, the value of confidence is inversely related to support. It is known that the rules with the highest confidence (98%) have a high lift, but the support value is relatively low compared to other rules.

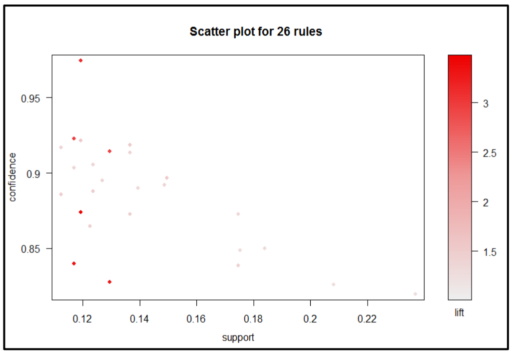


Figure 6. Scatter plot of the parameter by scheme 2

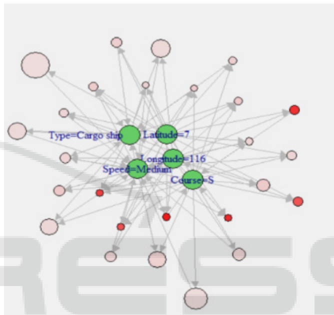


Figure 7. Rules pattern by scheme 2

The pattern rules for scheme two are presented in Figure 7. The image is more complicated than in scheme one because more arrows indicate the combination of items set for a maximum of 4. There are six red circles which mean the rules with the highest lift. Besides that, there are rules with the highest confidence (the most extensive circle size) with Latitude = 7, then Speed = Medium.

4 CONCLUSION

The association rules are successful in analysing the vessel movements. The pattern based on the frequency of item which occurs together show the prediction of the next to ship characteristics. The outstanding lift score is obtained by maximum length of item = 4, support = 0.1994, confidence = 87.39%. The rule state is if latitude = 7, longitude = 116, type = cargo ship, then course over ground = South. The result is appropriate to detect the pattern of vessel motion. It will simplify the officers to monitor and control traffic lines in Lombok Strait.

Furthermore, it useful for an early warning system to prevent the accident in the sea trade route.

ACKNOWLEDGEMENTS

The author would like to thank AISITS Surabaya for providing data sets, and Grant supported this work for the Department of Business Statistics 2020 ITS Surabaya.

REFERENCES

Agrawal R, Imielinski T, and Swami A 1993 Mining association rules between sets of items in large databases *ser. ACM SIGMOD International Conference on Management of Data* 207–216.

Deng F, Guo S, Deng Y, Chu H, Zhu Q and Sun F 2014 Vessel track information mining using AIS data *International Conference on Multisensor Fusion and Information Integration for Intelligent Systems (MFI)* 1-6.

Feixiang Z 2011 Mining ship spatial trajectory patterns from AIS database for maritime surveillance *ser. Proceedings of 2nd Intl. conference on Emergency Management and Management Science* 772–775.

Gustisatya P 2017 Determining Anomaly Activities of Ships Based on Data Analysis from AIS *Final Project* (ITS).

Harahap M, Husein A M, Aisyah S, Lubis F R, Wijaya B A 2018 Mining association rule based on the diseases population for recommendation of medicine need *IOP Conf. Series: Journal of Physics: Conf. Series* 1007.

Mascaro S, A. E. Nicholson A E, Korb K 2013 Anomaly detection in vessel tracks using bayesian networks International Journal of Approximate Reasoning.

Margaret H D 2003 Data Mining: Introductory and Advanced Topics Prentice Hall.

Melita H, Marie O, Hilaire S T, Sean W and Elisa S 2013 Maritime Traffic Data Mining Using R *16th International Conference on Information (FUSION)* Turkey.

Riveiro M and Falkman G 2011 The role of visualization and interaction in maritime anomaly detection *IS&T/SPIE Electronic Imaging. International Society for Optics and Photonics* 78680M-78680M-12.