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Application of Association Rule Mining to Analyze Factors Affecting Student Evaluation Results in Ikat Weaving Subjects

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Abstract

Ikat weaving is a hereditary cultural practice that possesses significant market value. However, many young people currently perceive ikat weaving as a profession suited for those who lack formal education, leading to a reluctance to engage in fabric weaving. SMA Negeri 1 Kambera has taken proactive steps by incorporating ikat weaving into the school curriculum. This initiative faces various challenges, including differences in family backgrounds, levels of interest, and proficiency in the Sumba language, all of which can potentially impact students' understanding and learning outcomes. At present, the relationship between these factors and student evaluation results is seldom analyzed. Therefore, this study aims to identify patterns in the factors influencing student evaluation outcomes in ikat weaving subjects by employing Association Rule Mining to analyze the relationships among variables such as family background, gender, ethnicity, student interests, and Sumba language skills. The analysis, conducted with a support threshold of 0.3 and a confidence level of 0.6, revealed that factors such as learning interest, gender, and family background have a strong association with evaluation performance. Female students tend to exhibit higher interest and achieve better evaluation results, while students from non-weaving families generally fall into the category of satisfactory grades. Nevertheless, non-weavers still have the potential to attain good grades if they belong to the Sumba tribe and possess proficiency in the Sumbanese language.

***Keywords**: Ikat weaving, Association Rule Mining, Apriori*

1. Introduction

Ikat weaving is a cultural heritage of East Nusa Tenggara that needs to be preserved through education. Local culture-based education can strengthen national identity and prevent cultural degradation due to the influence of globalization [1]. Research by Manarfa & Lasaiba (2023) states that incorporating regional cultural wisdom into the learning system can strengthen students' understanding of the importance of culture [2]. However, at this time many young people think that ikat weaving is a job for those who do not go to school so they are reluctant to weave cloth [3].

SMA Negeri 1 Kambera is one of the schools that has taken proactive action by including ikat weaving into the compulsory curriculum with the intention of preserving cultural heritage as well as improving students' knowledge and skills. In the implementation of this program, there are still several challenges, such as differences in students' backgrounds, both in terms of family, interests, and Sumbanese language skills. Many students do not come from weaver families, so they lack basic understanding or practical experience related to ikat weaving. In addition, limitations in the use of the Sumba language are also an obstacle, considering that the explanation of the material is often delivered in the Sumba language. This condition can affect students' understanding and learning outcomes. However, the relationship between these factors and student learning outcomes is still rarely analyzed in depth. Therefore, it is important to identify patterns of relationships with factors that affect students' evaluation outcomes in order to estimate their learning outcomes. Thus, teachers can design a learning process that is more targeted and in accordance with the characteristics of students.

Based on this, the author uses Association rule mining as one of the data analysis techniques in data mining that has been proven effective in analyzing datasets and finding hidden patterns that can be used to maximize the learning process. Research by Marthasari (2016) proves that the use of the Association rule mining method with a priori algorithms can identify the relationship between various variables (school origin, parental work and academic status) on student activeness [4]. In addition, research by Wang et al. (2022), also managed to find an important relationship between student behavioral factors and their academic performance, thus providing a basis for better decision-making in education management [5]. This shows the relevance of using the Association Rule Mining method in the context of learning ikat weaving. By applying the Association Rule Mining method, this study aims to be able to find hidden patterns in the factors that affect the results of student evaluation in ikat weaving subjects.

2. Theoretical foundations

2.1. Ikat weaving

Sumba ikat weaving is a type of East Sumba cultural fabric that has been inherited from generation to generation and still exists today. The process of making ikat weaving is still made manually with traditional techniques. This process requires skill, precision, and a good understanding of patterns. In daily life, the people of Sumba use ikat woven cloth not only for fashion, but also for traditional and cultural purposes such as marriage celebrations and the delivery of the deceased. In the context of learning, students who learn ikat weaving must understand the stages of work, such as designing motifs, tying yarns, dyeing, and weaving fabrics [6].

2.2. Learning Pattern

Learning Pattern is a series of learning of a student that is carried out continuously and becomes a tendency. Learning patterns are a way to find out the factors that students learn and understand something. Learning patterns reflect students' attitudes, styles, and behaviors in learning that, whether consciously or unconsciously, have a direct impact on their learning process [7]. Learning patterns can also refer to how students absorb, understand, and apply the knowledge they get from teachers. This pattern can be influenced by various factors such as teaching methods, learning environment, and individual characteristics or attitudes of students.

2.3. Data Mining

Data Mining is a technique used to extract hidden information or patterns from a large data set so that it can become useful information [8]. Data mining is also often referred to as Knowledge Discovery in Data base (KDD). KDD is an activity that includes data collection, data usage, history to find regularity, patterns or relationships in large data sets [9]. In general, the KDD process consists of the following steps:

1. Data selection, the collection of relevant data obtained from databases.
2. Data cleaning, inconsistent data cleaning process or irrelevant data.
3. Data integration, the process of combining data from various databases into one new database.
4. Data transformation, the process of data being transformed into a suitable format to be processed in data mining.
5. Data mining, a process in which methods are applied to find valuable knowledge from data.
6. Pattern recognition evaluation, to identify interesting patterns so that they can be presented in a knowledge-based way.
7. Knowledge presentation is the stage of visualization and presentation of knowledge obtained about the techniques used by the user.

2.4. Association Rule Mining

Association Rule Mining is a technique in data mining that is used to find the rules of association between a combination of items. Association Rule Mining is often applied in various fields, such as business, health, education, and technology, to find significant associations or associative patterns between variables in a dataset. In the context of education, ARM has been shown to be effective for analyzing students' learning patterns. For example, previous research showed that ARM can identify student learning activities that correlate with academic outcomes [10].

2.5. Priori

A priori algorithms are one of the algorithms of the Association Rule Mining technique introduced by Agrawal and Srikant in 1994. This algorithm is a way to determine patterns or relationships in data [11]. This technique is often used to look at habits or patterns that often appear together in the data. There are two main processes in a priori algorithm, namely:

a. Join (Merge), In this process each item is combined with other items until no more combinations are formed.
b. Prune (Pruning), In this process, the results of the combined items are then trimmed using the minimum support that has been determined by the user.

The rules of association are formed based on two main metrics, as follows:
• **Support:** the percentage of transactions that contain a specific combination of items, calculated by the formula:

$$\mathbf{Support(A)} = \frac{\textbf{Number of transactions that contain item A}}{\textbf{Total number of transactions}} \quad (1)$$

• **Confidence:** the probability of item B appearing after it is known that item A occurred, calculated as:

$$\mathbf{Confidence(A \rightarrow B)} = \frac{\mathbf{Support(A \cap B)}}{\textbf{Support A}} \quad (2)$$

In addition, the Lift Ratio metric is also used to measure the strength of associations between items:

$$\mathbf{Lift(A \rightarrow B)} = \frac{\mathbf{Support(A \cap B)}}{\mathbf{Support(A) \times Support(B)}} \quad (3)$$

Elevator > 1 indicates a strong and positive relationship between A and B.

A priori works by generating itemset combinations from level 1-itemset (C1), then increasing to a higher level (2-itemset, 3-itemet, etc.) as long as it still meets the minimum support value. The best combination is then used as an association rule to describe the pattern of relationships between variables in the dataset.

3. Research Methodology

This study uses a quantitative approach with an exploratory method to find patterns of relationships between factors that affect the results of student evaluation in the subject of ikat weaving at SMA Negeri 1 Kambera. The analysis technique used is Association Rule Mining (ARM) with a priori algorithm, which is able to identify association rules from categorical data that has been binary encoded. The following is the flow in this study:

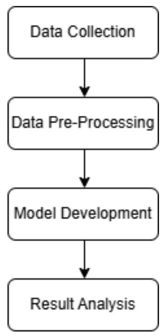

Fig. 1: Research flow

3.1. Data Collection

Data collection in this study was carried out through three main methods, namely questionnaires, interviews, and documentation. The questionnaire method was distributed to 154 students of class X to obtain primary data related to the independent variables studied, such as family background (weaver or not), gender, ethnicity, interest in ikat weaving lessons, and Sumba language skills. In addition, semi-structured interviews were conducted with local principals and content teachers to gain a deeper understanding of the implementation of ikat weaving learning and the various challenges faced in the field. The documentation method is used to collect data on the results of student evaluation results in the subject of ikat weaving for the 2023/2024 school year, which is a reference in the analysis of the relationship between variables.

3.2. Pra-Processing Data

Pre-processing is carried out to check the completeness of the data. If the data is incomplete, then the data collection process must be repeated so that it is eligible for analysis. Furthermore, if the data collected is complete, it will be continued at the modeling stage.

3.3. Model Development

At this stage, a priori algorithm is used as a method of calculating association rules to identify patterns in student data by utilizing the Google colab tool as a Python-based data analysis platform. The system is designed to be able to read student data in .csv format, clean and convert data, and carry out the process of finding patterns of relationships between variables such as family background, gender, ethnicity, learning interests, Sumba language skills and evaluation results. The results of the analysis are filtered based on support, confidence, and lift values, then presented in the form of a table and can be exported to CSV or Excel format for documentation purposes.

3.4. Results Analysis

Once the association rules are found, the results are analyzed so that they can be used to provide recommendations in improving ikat weaving learning strategies.

4. Results and Discussion

4.1. Data Collection

In the first stage of this study, this research uses questionnaire results data obtained from 154 students of the Ikat Weaving class X subject at SMAN 1 Kambera. The data consisted of several attributes, namely family background, gender, ethnicity, interest in ikat weaving, Sumatran language skills, and student evaluation results. The results of the evaluation are divided into three categories: Adequate, Good, and Excellent. The following is the raw dataset that has been collected.

Table 1. Raw Dataset

No	Name	Family	JK	Ethnic group	Interest	Sumba language	Value
1	Fransisco Andaluri	Weavers	L	Sumba	Neutral	Yes	78
2	Maricha Tawuru May	Non-weavers	P	Sumba	Neutral	Yes	81
3	Maria Putti yani	Non-weavers	P	Sumba	Neutral	Yes	82
4	Lamba load from	Non-weavers	P	Sumba	Neutral	Yes	79
…	…	…	…	…	…	…	…
153	Deansi R. May Hina	Weavers	P	Sumba	Tetarik	Yes	84
154	Raymond R. S. S. S.	Non-weavers	P	Sumba	Neutral	Yes	83

4.2. Pra-Processing Data

At this stage, the data that has been collected is converted into binary format i.e. 0 and 1. In this study, the variables used are divided into several categories, which can be seen in the table below:

Table 2. Variable category

Variabel	Label	Code
Family background	Weavers	1
	Non-Weaver	0
Gender	Woman	1
	Man	0
Ethnic group	Sumba	1
	Non sumba	0
Interest in Ikat Weaving	Interested	1
	Neutral	1
	Not Interested	1
Can speak Sumba	Bisa	1
	Cannot	0
Evaluation/Results	Enough(69-76)	1
	Good(77-84)	1
	Excellent	1

Pre-processing of data in this study aims to prepare data so that it can be used in the analysis process with a priori algorithm. The initial data is stored in .xlsx format and loaded into a programming environment using the Pandas and NumPy libraries on the Google Colab platform. Here is the initial code done for the reading of the file that contains

```
import pandas as pd
import numpy as np
df = pd.read_excel('/Belajar2.xlsx')
df.head()
```

Fig. 2: Python code for reading files

a dataset of factors that affect the student's grade, the python command used is:

This step is important to ensure that the data is readable successfully, has the appropriate structure, and is ready for further processing, such as conversion to binary forms, variable labeling, and handling of blank values or categories. After the student dataset is loaded using the pd.read_excel() function, the next step is to perform an initial check of the contents of the data using df.head(). This function displays the first five rows of the dataset in the form of the following table:

Each row represents one student respondent, while each column represents a category of variables that have been converted into binary (0/1) for analysis purposes with a priori algorithm. Before further analysis is carried out, the data needs to be cleaned of columns that are not analytically relevant. In this case, the "Name" column has no numerical value and does not contribute to the process of forming association rules. Therefore, the column was deleted. This step is done with the following code:

	Nama	PENENUN	NON PENENUN	PRIA	WANITA	SUMBA	NON SUMBA	TERTARIK	NETRAL	TIDAK TERTARIK	BISA	TIDAK BISA	CUKUP	BAIK	SANGAT BAIK
0	Fransisco Andaluri	1	0	1	0	1	0	0	1	0	1	0	0	1	0
1	Maricha Tawuru May	0	1	0	1	1	0	0	1	0	1	0	0	1	0
2	Maria Putti Yani	0	1	0	1	1	0	0	1	0	1	0	0	1	0
3	Adinda Lambalodu	0	1	0	1	1	0	0	1	0	1	0	0	1	0
4	Larisa Karari Aji	0	1	0	1	1	0	0	1	0	1	0	1	0	0

Fig. 3: Dataset retrieval results

```
df = df.drop(columns=['Nama'])
df.head()
```

Fig. 4: Python code to delete the name column

This step is important in the pre-processing stage, because a priori algorithms only work with binary categorical data, and the presence of non-numerical data such as names will actually interfere with the calculation of support and confidence. Thus, the data becomes cleaner, structured, and ready for the next stage of analysis. The following is a table after the name column in the table is removed:

	PENENUN	NON PENENUN	PRIA	WANITA	SUMBA	NON SUMBA	TERTARIK	NETRAL	TIDAK TERTARIK	BISA	TIDAK BISA	CUKUP	BAIK	SANGAT BAIK
0	1	0	1	0	1	0	0	1	0	1	0	0	1	0
1	0	1	0	1	1	0	0	1	0	1	0	0	1	0
2	0	1	0	1	1	0	0	1	0	1	0	0	1	0
3	0	1	0	1	1	0	0	1	0	1	0	0	1	0
4	0	1	0	1	1	0	0	1	0	1	0	1	0	0

Fig. 5: Table after the name column is deleted

4.3. Model Creation

Once the data is converted into binary, the next step is to perform an initial analysis of the frequency of occurrence of each item in the dataset. The goal is to find out how often each category appears in the entire student data. The next step is to calculate the frequency with which each item appears in the dataset. It aims to find out how dominant each characteristic is in the student population before applying an A priori algorithm. The codes used are as follows:

```
# Find Frequency of Items
df_encoded = df.copy()
df_encoded.sum()
```

Fig. 6: Python code for calculating frequency

This information will be the basis for calculating the support count of each item or combination of items at the next stage in the A priori algorithm. The following is an image of the results of the calculation of the frequency of occurrence.

	0
PENENUN	51
NON PENENUN	103
PRIA	75
WANITA	79
SUMBA	150
NON SUMBA	4
TERTARIK	87
NETRAL	46
TIDAK TERTARIK	20
BISA	141
TIDAK BISA	13
CUKUP	53
BAIK	84
SANGAT BAIK	17

Fig. 7: Frequency Calculation Results for Each Item

After knowing the frequency of each item, the next process is to perform the first iteration of the A priori algorithm to generate frequent itemsets or combinations of items that meet the support threshold. In this study, the minimum support used was 0.3 or 30%. Here is the python code used:

```
df_encoded = df.copy()
iteration1 = ar_iterations(df_encoded, num_iter=1, support_value=0.3, iterationIndex = None)
iteration1
```

Fig. 8: Python code for iteration 1

The above program code is used to run the first iteration process in the frequent itemset lookup using the Association Rule Mining approach. The initial step begins with creating a copy of the data that has been converted to binary form via the command df_encoded = df.copy(). This copy aims to maintain the integrity of the original data, so that the analysis process can be carried out without affecting the main dataset. Next, the ar_iterations() function is invoked with several parameters, namely: df_encoded as input data, num_iter=1 which indicates that this process is the 1st iteration, support_value=0.3 which means that only itemset with a support value of at least 30% will be further processed, and iterationIndex=None which indicates that the iteration index will be determined automatically by the system. The results of this process are stored in an iteration1 variable, which will contain a single item combination (1-itemset) that meets the support threshold and is ready for analysis at the next stage. This process is the first step in building an association model using a priori algorithm.

The following figure shows the results of the first iteration of the A priori algorithm, which is a list of 1-itemsets that meet the minimum support value of ≥ 0.3 (30%).

	index	Support	length
0	SUMBA	0.974026	1
1	BISA	0.915584	1
2	NON PENENUN	0.668831	1
3	TERTARIK	0.564935	1
4	BAIK	0.545455	1
5	WANITA	0.512987	1
6	PRIA	0.487013	1
7	CUKUP	0.344156	1
8	PENENUN	0.331169	1

Fig. 9: Results of iteration 1

All items in Figure 9. It has support above 0.3, so it passes to the next stage for the formation of 2-itemsets. The following is the code used for the formation of the 2-itemset.

```
df_encoded = df.copy()
iteration2 = ar_iterations(df_encoded, num_iter=2, support_value=0.3, iterationIndex=iteration1.index)
iteration2
```

Fig. 10: Python code for iteration 2

0	(SUMBA, BISA)	0.909091	2	0.933333	1.019385
1	(SUMBA, NON PENENUN)	0.642857	2	0.660000	0.986796
2	(BISA, NON PENENUN)	0.616883	2	0.673759	1.007368
3	(SUMBA, TERTARIK)	0.558442	2	0.573333	1.014866
4	(BISA, TERTARIK)	0.532468	2	0.581560	1.029429
5	(SUMBA, BAIK)	0.525974	2	0.540000	0.990000
6	(SUMBA, WANITA)	0.500000	2	0.513333	1.000675
7	(BISA, BAIK)	0.493506	2	0.539007	0.988180
8	(SUMBA, PRIA)	0.474026	2	0.486667	0.999289
9	(BISA, PRIA)	0.467532	2	0.510638	1.048511
10	(BISA, WANITA)	0.448052	2	0.489362	0.953946
11	(NON PENENUN, BAIK)	0.389610	2	0.582524	1.067961
12	(NON PENENUN, WANITA)	0.363636	2	0.543689	1.059850
13	(SUMBA, CUKUP)	0.337662	2	0.346667	1.007296
14	(SUMBA, PENENUN)	0.331169	2	0.340000	1.026667
15	(TERTARIK, WANITA)	0.318182	2	0.563218	1.097919
16	(BAIK, WANITA)	0.318182	2	0.583333	1.137131
17	(BISA, CUKUP)	0.311688	2	0.340426	0.989161
18	(NON PENENUN, PRIA)	0.305195	2	0.456311	0.936958

Fig. 11: Results of iteration 2

The results are shown in Figure 11, which shows the combination of two items that meet the support value of at least 30%. Each row lists the item combination, support value, itemset length (length=2), and confidence and lift values. The combination with the highest support is (SUMBA, BISA) of 0.91 with a confidence of 0.93, indicating that the majority of students from Sumba can also speak Sumba. Several other combinations such as (NON-WEAVER, FEMALE) and (INTERESTED, FEMALE) also indicate a > 1 lift, indicating a positive relationship and potentially becoming a meaningful association rule. This result became the basis for the formation of association rules at a later stage.

Once a 2-itemset combination is found that meets the support threshold, the process proceeds to the third iteration to form a 3-itemset combination. The aim of this step is to explore a more complex pattern of relationships between three variables at once, so as to uncover more specific and meaningful relationships in the context of student evaluation results. The 3-itemset combination is formed based on items that passed in previous iterations, and only combinations that meet the minimum support value will be retained for further analysis.

```
iteration3 = ar_iterations(df_encoded, num_iter=3, support_value=0.3, iterationIndex=iteration2['index'])
iteration3
```

Fig. 12: Python code for iteration 3

	index	Support	length	Confidence	Lift
0	(BISA, NON PENENUN, SUMBA)	0.610390	3	0.666667	0.996764
1	(BISA, SUMBA, TERTARIK)	0.525974	3	0.574468	0.589787
2	(BAIK, BISA, SUMBA)	0.487013	3	0.892857	0.975177
3	(BISA, PRIA, SUMBA)	0.461039	3	0.503546	1.033948
4	(BISA, SUMBA, WANITA)	0.448052	3	0.489362	0.502411
5	(BAIK, NON PENENUN, SUMBA)	0.370130	3	0.678571	1.014563
6	(BAIK, BISA, NON PENENUN)	0.363636	3	0.666667	0.728132
7	(NON PENENUN, SUMBA, WANITA)	0.350649	3	0.524272	0.538252
8	(BISA, NON PENENUN, WANITA)	0.324675	3	0.354610	0.530193
9	(SUMBA, TERTARIK, WANITA)	0.318182	3	0.326667	0.578238
10	(BISA, CUKUP, SUMBA)	0.311688	3	0.340426	0.989161
11	(BAIK, SUMBA, WANITA)	0.305195	3	0.559524	0.574444

Fig. 13: Results of iteration 3

The third iteration managed to find 12 3-itemset combinations that met ≥ 30% support. Some combinations show a high confidence value, but most have a < 1 lift, which means the relationships between items are not yet statistically strong. However, combinations such as (GOOD, CAN, SUMBA) remain important because they reflect the characteristics of students who are likely to succeed in the evaluation of ikat weaving learning.

4.4. Results Analysis

Once the data is encoded in binary format and analyzed through several iterative stages, starting from 1-itemset to 3-itemset, with a minimum support threshold of 30% and a minimum confidence of 60%. The results of each iteration are analyzed based on support, confidence, and lift values to determine the strength of associations between items.

a. 1 Item-set

In the first iteration, the individual items that appear most often are found. The item with the highest support score was SUMBA (97%), followed by BISA (91%), and NON WEAVER (66%). This shows that the majority of students who take ikat weaving lessons are students who come from the Sumba tribe, have the ability to speak Sumba, and do not come from a weaver family.

b. 2 Item-set

A number of combinations of two factors were formed that had a fairly strong association with the results of the evaluation. Some of the most prominent combinations are the relationship between interest in weaving lessons and female gender, which suggests that female students tend to have a higher interest in learning ikat weaving. In addition, it was found that female students also obtained more evaluation results in the "good" category, indicating the possibility of the influence of gender factors on learning outcomes. Meanwhile, students from non-weaver families tend to score in the "adequate" category, which shows that family background still has an influence on understanding local cultural skills.

c. 3 Item-set

More complex and specific relationship patterns were found. One combination that passed the threshold and had a ≥ 1 elevator score was a combination of students with a non-weaver background, Sumba tribe, and obtained "good" evaluation results. This pattern indicates that students who do not come from weaver families still have the potential to succeed in learning weaving, as long as they come from a strong cultural environment (such as the Sumba tribe). This reinforces the idea that local cultural factors can be a counterbalance to the limitations of family backgrounds in supporting the success of cultural heritage-based learning.

5. Conclusion

This study aims to find the pattern of relationships between various characteristic factors of students such as family background, gender, ethnicity, interest in lessons, and Sumba language skills with the results of their evaluation in the subject of ikat weaving at SMA Negeri 1 Kambera. The analysis was carried out using an A priori algorithm, with a minimum support value of 30% and confidence of 60%, which produces association rules from a combination of these factors.

Based on the results of the 1-itemset to 3-itemet iterations, it was found that the most relevant and statistically meaningful patterns were found in the combination of 2-itemset and 3-itemset. For example, female students show more interest in weaving lessons and tend to achieve evaluation results in the "good" category. In addition, students from non-weaver families get more "adequate" grades, but still have the opportunity to achieve "good" grades if they come from the Sumba tribe and have the ability to speak Sumba. This suggests that the influence of local culture can support learning success even if students do not have a weaver family background.

These findings provide important benefits in the context of education, namely as a decision-making basis for teachers and schools in designing more contextual, adaptive, and data-based learning strategies. Teachers can figure out which factors need to be considered to help students who are potentially left behind or less interested. In addition, this study also supports the preservation of local culture by providing evidence that culture-based learning can be increased in effectiveness if students' background factors are analyzed and understood in depth. Thus, the patterns found not only strengthen academic understanding, but also make a real contribution to the preservation of ikat weaving culture among the younger generation.

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