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Comparison Of Apriori And Fp-Growth Algorithms In Determining Package Menus At Sate Perawan Restaurant Sawangan Raya

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ABSTRACT

The culinary creative industry holds promising prospects as it is a necessity for society. However, the variety of menu items and high customer demand lead to slow ordering processes, which hinder service at Rumah Makan Sate Perawan. Additionally, some menu items are less popular among customers. To address these issues, a system is needed to assist in determining food and beverage package menus based on association rules. This system aims to facilitate business owners in organizing packages and improving sales. This study employs the Apriori and FP-Growth algorithms, using sales transaction data collected over a four-month period. The research applies a minimum support of 0.1 for food, 0.01 for beverages, and a minimum confidence of 0.6 for both categories. The results indicate that there is no significant difference between the two algorithms in terms of the generated packages, lift ratio evaluation, and runtime. In the food category, 5 association rules were generated with an average lift ratio of 1.1929, while in the beverage category, 2 rules were generated with an average lift ratio of 1.8990.

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1. INTRODUCTION

The presence of creative industries in Indonesia is growing with various innovative ideas and ideas. The creative industry is a process of generating ideas and creativity carried out by individuals or groups of people, resulting in works that are then used as economic products. Some examples of creative industries are culinary, craft, fashion, advertising, photography, music etc. According to the Ministry of Tourism and Creative Economy, of the many creative industry subsectors in Indonesia, there are 3 sub sectors that are growing rapidly and leading in the development of the nation's creative economy, including culinary around 41%, fashion around 17%, and crafts as much as 14.9% [1]. The culinary creative industry is quite promising because it includes everyone's primary needs [2]. Along with the times, many companies, especially in the culinary field, are innovating products in the food and beverage menu to increase sales [3]. Due to the large number of culinary enthusiasts and diverse menu items, customers take a long time to decide on an order, and service is hampered [4].

Sate Perawan Restaurant located in Sawangan Raya was established in 2018 [5] which started with 24 menus until now there are 28 menus for food and drinks. Rumah Makan Sate Perawan is always crowded with buyers, especially during lunch hours, before office hours until the evening. Especially on weekends, it is more crowded with buyers and makes customers wait a long time for orders. Food and beverage menus are still sold separately and there are menus that are less desirable. However, based on sales transaction data, services can be improved by determining the most frequently ordered food and beverage package menu with the aim of being a recommendation to make it easier for customers to order food and drinks [3]. As for the less desirable menu, it will be combined with a menu that is high in demand with the aim that the less desirable menu can be an attraction for consumers so that it can increase sales of certain menus [6].

The variety of food and beverage menus owned by Sate Perawan Restaurant makes it difficult for customers to determine the menu they want to buy and there are menus that are less attractive. Based on the above problems, the author proposes to create a web-based application using the Apriori Algorithm and Frequent Pattern Growth (FP- Growth) Algorithm that can determine the strongest combination pattern of food and drinks based on association rules. This web-based application can help create a package menu based on data inputted by the user.

This research refers to research that has been done by I. Musdalifah and A. Jananto [7] conducted research related to the formation of customer shopping cart association patterns to ensure inventory at PT Multi Lestari by analyzing the comparison of the apriori algorithm and the fp-growth algorithm using RStudio software. Meanwhile, this research is related to determining the package menu at restaurants in order to increase sales and make it easier for customers to choose a menu. This research uses the python programming language which has python programming language has an easy syntax writing besides that python also has a complete library [8]. in addition, the evaluation used is the lift ratio and uses Visual Studio Code and Google Collaboratory software.

In several other studies that have been conducted, discussing the goods layout system by Mardianti & Fauzi [9], Siti Aisyah & Normah [10], Sena et al [11], and Munanda & Monalisa [12]. Combination system by Qomariah et al [13], and Nur Harahap & Sulindawaty [14]. Recommendation system by Setiawan & Mulyanti [15]. Stock management system by Lestari & Hafiz [16], Kurniawati et al [17], and Awaliyah & Handayanna [18]. Comparative analysis of apriori and fp-growth algorithms by Musdalifah & Jananto [7].

The following is the minimum support and minimum confidence to get association rules, namely at minimum support>= 2% and minimum confidence <= 60% research conducted by Siti Qomariah et al, Aji & Rizka, Siti Aisyah & Normah and Fitri & Rahmat. Whereas for minimum support >= 17% and minimum confidence >= 70% the research was conducted by Ade & M. Hafiz, Laela et al, Rizky et al, Paujiah & Sulindawaty, Siti Awaliyah & Frisma, Elvira Munanda & Siti Monalisa, and Ifa Musdalifah & Arief Jananto.

2. METHOD

At this stage is the data and research flow in the form of algorithms used to support research in determining the food and beverage package menu.

A. Data

The data source in this study is data from Sate Perawan Restaurant in Sawangan Raya from December 2023 to March 2024 with documentation techniques in the form of data collection per transaction. This data has 416 rows and has 28 menus. The description of the data from Rumah Makan Sate Perawan in Sawangan Raya used in this study is presented in table 1.

Table 1. Description of data

Item	Description
A	Item A describes Tengkleng kambing
B	Item B describes sate kambing bumbu kecap
C	Item C describes sate kambing bumbu kacang
D	Item D describes Sate hati bumbu kecap
E	Item E describes Sate hati bumbu kacang
F	Item F describes Sate ayam bumbu kecap
G	Item G describes Sate ayam bumbu kacang
H	Item H describes Sate Daging Sapi bumbu kecap
I	Item I describes Sate Daging Sapi bumbu kacang
J	Item J describes Sop kambing
K	Item K describes Gulai kambing
L	Item L describes Tongseng kambing
M	Item M describes Tongseng ayam

Item	Description
N	Item N describes Nasi Putih
O	Item O describes Lontong
P	Item P describes Kerupuk
Q	Item Q describes Kuah sop
R	Item R describes Kuah gulai
S	Item S describes Aqua (air mineral)
T	Item T describes Es teh tawar
U	Item U describes Es teh manis
V	Item V describes Teh manis hangat
W	Item W describes Es jeruk
X	Item X describes Air jeruk hangat
Y	Item Y describes Es lemon tea
Z	Item Z describes Lemon tea hangat
AA	Item AA describes Jeruk nipis hangat
AB	Item AB describes Es Jeruk nipis

B. Algorithms

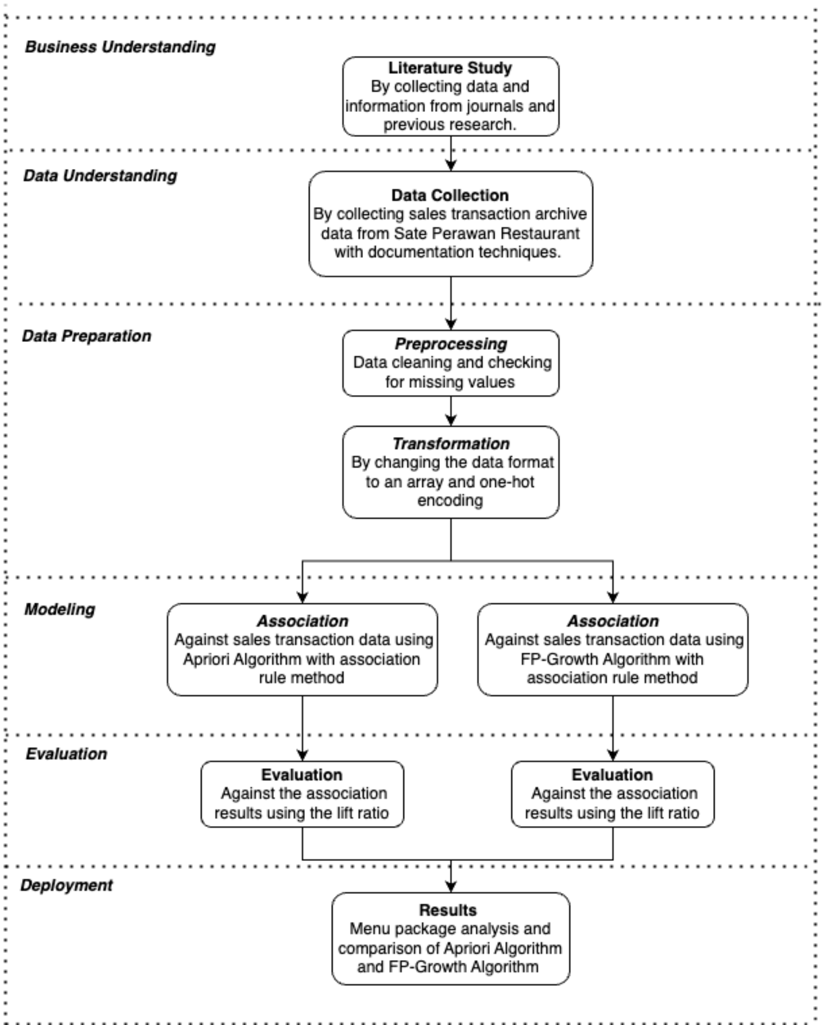

Figure 1. flow of research

Cross Industry Standard Process Model for Data Mining (CRISP-DM) is a strategic analysis process used to solve research problems or problems of a business or company [19]. This research was conducted using CRIPS-DM with 6 stages presented in Figure 1.

1. Business Understanding Phase

In the literature study, this research seeks and uses information related to data collection techniques with documentation and algorithms to be used such as the apriori algorithm and the fp-growth algorithm from journals and previous research.

2. Data Understanding Phase

In the data collection stage, the data collected in this research is primary data. Data is collected using documentation techniques in the form of sales transaction archives originating from the Sate Perawan Restaurant. Data comes from transaction data for 4 months from December 2023 to March 2024.

3. Data Preparation Phase

In the Data Preparation stage, there are two (2) sub-stages: preprocessing and transformation. In the preprocessing stage, this study performs data cleaning and checks for missing values. Subsequently, in the transformation stage, the data format is changed into an array, and transaction data is encoded using one-hot encoding to facilitate the modeling process.

4. Modeling Phase

After the Data Preparation stage, the next step is to model the apriori algorithm and the fp-growth algorithm. apriori algorithm has stages, namely determining the minimum support, forming candidate itemsets, forming combinations of itemsets that meet the support value. While the fp-growth algorithm has stages, namely conditional pattern base generation, conditional FP-tree generation and frequent itemset search. Then in the last stage, namely finding association rules by looking for support values and confidence values.

5. Evaluation Phase

The stage after getting the results of modeling, namely looking for the lift ratio value to determine whether the association rule is valid or not. If it is greater than 1, it indicates the benefit of the rule or the higher the lift ratio value, the greater the strength of the association.

6. Deployment Phase

The last stage is the deployment phase, at this stage analyzing the most accurate algorithm for determining the package menu. The following are the manual stages of the apriori algorithm and the fp-growth algorithm in determining the food and beverage package menu

a. Apriori Algorithm

Sample data goes through a data transformation stage in the form of one-hot encoding which aims to convert values into binary, namely with symbols 0 and 1. In table 4.3 one-hot encoding, symbol 1 states that there is a transaction and 0 states that no transaction has occurred [20].

Table 2. One Hot Encoding

Transactions	**AA**	**B**	**F**	**G**	**J**	**K**	**L**	**N**	**P**	**Q**	**S**	**T**	**U**	**V**	**W**	**X**
1	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0
2	1	1	0	0	1	0	0	0	0	0	0	1	1	0	0	0
3	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	1
4	0	1	0	0	1	0	0	0	0	0	0	1	1	0	0	1
5	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0
6	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0
7	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0
8	0	0	1	0	0	1	1	1	0	0	0	0	0	0	1	0
9	0	1	0	0	0	0	1	1	1	0	0	1	0	0	0	0
10	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0
Count	**2**	**7**	**1**	**1**	**4**	**1**	**4**	**3**	**1**	**1**	**1**	**6**	**3**	**2**	**1**	**2**

The next stage is the formation of 1-itemset candidates, 2-itemset combination candidates,3-itemset combination candidates, and so on until there are no more combinations that meet the minimum support of 0.3. Support shows how often an item appears in a database [21]. In table 3 arethe results of calculating candidate itemsets that meet the minimum support using formula (1), the following formula is used [22]:

$$\text{Support (A)} = \frac{\text{number of transactions containing A}}{\text{Total Transactions}} \text{x}100\% \qquad (1)$$

Tabel 3. result of the calculation of candidate itemsets

No.	Item	Support Count	Support
1	B	7	0.7
2	J	4	0.4
3	L	4	0.4
4	N	3	0.3
5	T	6	0.6
6	U	3	0.3
7	B,J	4	0.4
8	B,T	5	0.5
9	J,T	3	0.3
10	B, J, T	3	0.3

After all the high-frequency patterns [14] are found, the next step is to form association rules to look for relationships between items in a data set [[23]. To form an association rule, a confidence value is required, which is using the formula (2) as follows:

$$\text{Confidence (B|A)} = \text{P(B|A)} = \frac{\text{sum of transactions A and B}}{\text{Sum of Transaction A}} \text{x}100\% \qquad (2)$$

The following are the results of the calculation of the confidence value of 2 itemsets in table 4 and table 5 results of the confidence value of 3 itemsets.

Table 4 itemset association rule

Rules	Confidence in %	
if you order B , you will order J	4 per 7	57.1
if you order J , you will order B	4 per 4	100.0
if you order B , you will order T	5 per 7	71.4
if you order T , you will order B	5 per 6	83.3
if you order J , you will order T	3 per 4	75
if you order T , you will order J	3 per 6	50.0

Table 5 itemset association rule

Rules	**Confidence in %**	
if you order B and J you will order T	3 per 4	75.0
if you order J and T you will order B	3 per 3	100.0
if you order T and B you will order J	3 per 5	60.0
if you order J you will order T and B	3 per 4	75.0
if you order T you will order J and B	3 per 6	50.0
if you order B you will order J and T	3 per 7	42.9

Table 6 is the final association rule that meets the minimum confidence of 70% and the results of the lift ratio calculation with the formula [23] :

$$\text{Lift Ratio} = \frac{\text{Confidence } (A \cap B)}{\text{benchmark confidence}} \qquad (3)$$

$$\text{Benchmark Confidence} = \frac{\text{Number of Transactions containing BB}}{\text{Number of Transactions}} \qquad (4)$$

After getting the lift ratio value using formulas (3) and (4), it can be seen the strength levelof the association rule in table 6. If the lift ratio value is greater than 1, it indicates the benefit of therule or the higher the lift ratio value, the greater the strength of the association [24].

Table 6. Apriori Final Associations Rule

Rules	Support (%)	Confidence (%)	Lift Rasio
if you order J, you will order T dan B	30	75	1.50
if you order J , you will order B	40	100.0	1.43
if you order J dan T you will order B	30	100	1.43
if you order J , you will order T	30	75.0	1.25
if you order B dan J you will order T	30	75.0	1.25
if you order B , you will order T	50	71.4	1.19
if you order T , you will order B	50	83.3	1.19

In table 7 is the final apriori package menu which combines a package menu that is high insupport with a menu that is low in support which aims to make a menu that is less attractive to consumers so that it can increase sales of certain menus [6].

Table 7. Apriori Final Package Menu

No.	Package Menu	Less Popular	Lift Ratio
1	if you order J you will order T dan B	F	1.50
2	if you order J , you will order B	G	1.43
3	if you order J dan T you will order B	K	1.43
4	if you order J , you will order T	P	1.25
5	if you order B dan J you will order T	Q	1.25
6	if you order B , you will order T	S	1.19
7	if you order T , you will order B	W	1.19

B. FP-Growth Algorithm

FP-Growth algorithm is an alternative algorithm that can be used to determine the set of data that appears most often in a data set [12]. In the initial stage of the fp-growth algorithm, it is tofind frequent itemsets from sales data samples with a minimum support of 0.3. frequent 1 itemset can be seen in table 8.

Table 8. Frequent 1 itemset

Itemset	Sup.Count
B	7
J	4
L	4
N	3
T	6
U	3

Furthermore, table 9 is the result table of sorting the transaction table based on the frequent1-itemset that has been sorted descending {{B: 7},{T: 6},{J: 4},{L: 4},{N: 3},{U: 3}} and deletingmenus that do not meet the minimum support.

Table 9.Transactions that have been sorted

Transactions	Dataset
1	B, T
2	B, T, J, U
3	B, T, J
4	B, T, J, U
5	T, L
6	B
7	B, J, N
8	L, N
9	B, T, L, N
10	L, U

The information in table 9 can be used as a guide to build the fp-tree. An FP-Tree is formedfrom a root labeled null, a set of trees containing specific items, and a frequent header table [25]. The following figure 2 is the result of creating an fp-tree:

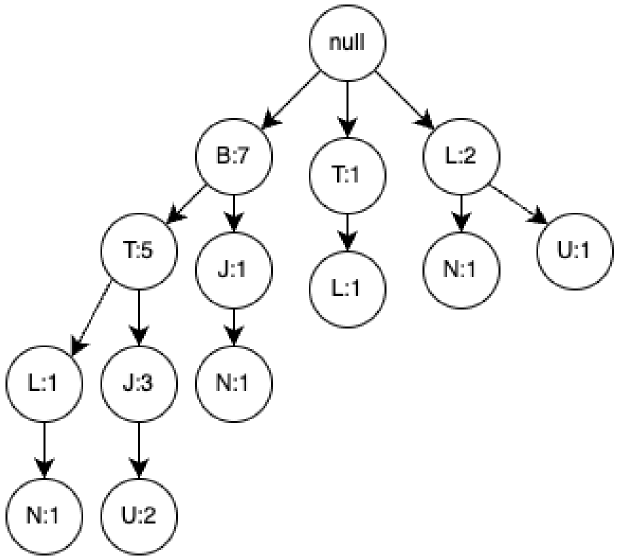

Figure 2. overall fp-tree

The next stage is the generation of a conditional pattern base which is done by looking back at the formation of the fp-tree that has been made before. In Figure 3 are the fp-tree of trajectories containing itemset table 9.

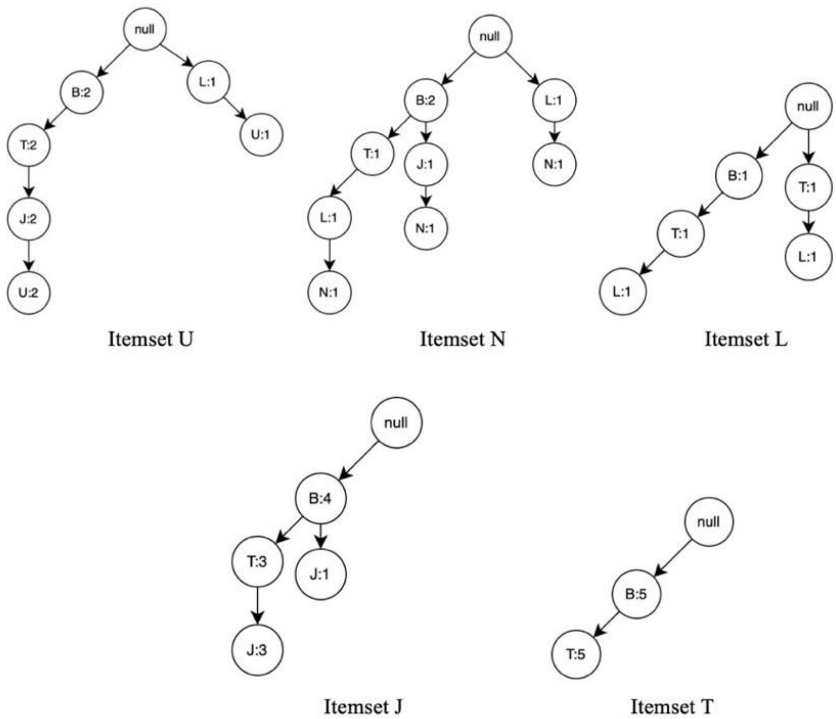

Figure 3. *fp-tree itemset*

At the conditional pattern base starting from the item with the lowest support count to the item with the highest support count. then at this conditional fp-tree stage, the support count of each item in each

Conditional Pattern Base is accumulated, and each item that has a greater support countequal to the minimum support count will be generated with a conditional FP-tree [7]. then at this frequent patterns stage, a combination of items with a conditional fp-tree is performed. Thefollowing table 10 is the result of the three:

Table 10. the result of the three

item	Conditional pattern base	Conditional fp-tree	Frequent patterns
U	{B,T, J :2}, {L:1}	-	
N	{B,T,L:1}, {B,J:1}, {L:1}	-	
L	{B,T:1},{T:1}	-	
J	{B, T:3},{B:1}	{B:4},{T:3}	{B,J:4},{T,J:3},{B,T,J:3}
T	{B:5}	{B:5}	{B,T:5}

After getting frequent patterns, the next step is to form association rules to find patterns, associations and relationships between the data. To form an association rule, a confidence value is required, which is the following formula:

$$\text{Confidence } (B|A) = P(B|A) = \frac{\text{sum of transactions A and B}}{\text{Sum of Transaction A}} \text{x}100\% \quad (2)$$

After obtaining the lift ratio value using formula (2.3), it can be seen the strength level of the association rules in table 11

Table 11. Final fp-growth Association Rules

Rules	Support (%)	Confidence (%)	Lift Rasio
IF {J] THEN {T,B}	30	75	1.50
IF {J} THEN {B}	40	100.0	1.43
IF {T,J} THEN {B}	30	100	1.43
IF {J} THEN {T}	30	75.0	1.25
IF {J,B} THEN {T}	30	75.0	1.25
IF {T} THEN {B}	50	71.4	1.19
IF {B} THEN {T}	50	83.3	1.19

Table 12 is the final fp-growth package menu which combines the high support package menu with the low support menu.

Table 12. Apriori Final Package Menu

No.	Package Menu	Less Popular	Lift Ratio
1	IF {J] THEN {T,B}	F	1.50
2	IF {J} THEN {B}	G	1.43
3	IF {T,J} THEN {B}	K	1.43
4	IF {J} THEN {T}	P	1.25
5	IF {J,B} THEN {T}	Q	1.25
6	IF {T} THEN {B}	S	1.19
7	IF {B} THEN {T}	W	1.19

3. RESULTS AND DISCUSSION

In Table 13 is a Load Dataset of Food and Beverages using Google Collaboratory. The data used is the resultof manual separation based on food and beverage categories. Food data has 416 rows and beverage data has 256 rows.

Table 13. Apriori Final Package Menu

No.	Food	Beverage
0	B	V
1	B, J	T, U, AA
2	B, J	T, X

No.	Food	Beverage
3	B, J	T, U, X
4	L	T, V
5	B, G	AA
6	B, J, N	W
7	F, K, L, N	T
8	B, L, N	S, U
9	L	T
10	B, J	S, T

The preprocessing stage is divided into 2, namely data cleaning and checking missing values. Data cleaningis done manually using excel by deleting several unnecessary items because it is feared that it can reduce the quality of the package results. The deleted items are in the food category, namely O, P, Q, R. Next, check the missing value and get the result that there is no missing value in the food and beverage dataset. Furthermore, the transformation stage is divided into 2, namely changing the data format and one-hot encoding. In Figure 4, it changes the form of data to be processed from a dataframe to an array to make it easier when doing one-hot encoding.

```
[[' B'],
 [' B', ' J'],
 [' B', ' J'],
 [' B', ' J'],
 [' L'],
 [' B', ' G'],
 [' B', ' J', ' N'],
 [' F', ' K', ' L', ' N'],
 [' B', ' L', ' N'],
 [' L'],
 [' B', ' J'],
 [' B', ' L', ' N'],
 [' F', ' G'],
 [' D', ' L'],
 [' C', ' F'],
 [' G', ' M', ' N'],
```

Figure 4. Change Data Format

One-hot encoding is one of the techniques used to convert previous data into a form of data that can be processed by the algorithm. In Figure 5 the data is converted into binary, namely with symbols 0 and 1, symbol 1 states that there is a transaction and 0 states that no transaction has occurred. In Figure 5 there are no items H and I because none of the transactions have occurred.

	A	B	C	D	E	F	G	J	K	L	M	N
0	0	1	0	0	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	1	0	0	0	0
2	0	1	0	0	0	0	0	1	0	0	0	0
3	0	1	0	0	0	0	0	1	0	0	0	0
4	0	0	0	0	0	0	0	0	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
411	0	0	0	0	0	0	1	1	0	1	0	1
412	0	0	0	0	0	1	0	0	0	1	0	1
413	0	0	0	0	0	0	0	1	0	0	0	1
414	0	1	0	0	0	0	0	0	0	1	0	1
415	0	0	0	0	0	0	1	0	0	0	0	0

Figure 5. one-hot encoding

at the modeling stage using two algorithms, namely the apriori algorithm and the fp-growth algorithm.

a. FP-Growth Algorithm

In Figure 6 is the process of finding frequent itemsets in order from the largest support to the smallest support with a minimum support of 0.1 and in Figure 7 displays the results of a minimum support of 0.01. Minimum support for food and drinks is made different because if the minimum support for food data is 0.01, it will result in 55 association rules. Meanwhile, if the minimum support for beverage data is 0.1, then there are no association

	support	itemsets
4	0.598558	(N)
0	0.423077	(B)
1	0.346154	(J)
7	0.300481	(N, B)
9	0.259615	(N, J)
2	0.247596	(L)

Figure 6. Frequent Itemset Food

Figure 8 is an association rule in the food category with a minimum confidence of 0.6 andproduces 5 rules with an average food lift ratio value of 1.1929. Then in Figure 9 is the associationrule in the food category with a minimum confidence of 0.6 and produces 2 rules with an average lift ratio value of 1.8990. The reason for using a minimum confidence of 0.6, so that it can use the highest minimum confidence but in the beverage category it can still produce rules.

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift
2	(B, J)	(N)	0.170673	0.598558	0.137019	0.802817	1.341252
1	(J)	(N)	0.346154	0.598558	0.259615	0.750000	1.253012
0	(B)	(N)	0.423077	0.598558	0.300481	0.710227	1.186564
3	(L)	(N)	0.247596	0.598558	0.165865	0.669903	1.119195
4	(G)	(N)	0.218750	0.598558	0.139423	0.637363	1.064831

Figure 7. Frequent Itemset Beverage

	support	itemsets
1	0.468750	(T)
2	0.261719	(U)
5	0.238281	(W)
0	0.156250	(V)
4	0.148438	(X)
6	0.128906	(S)

Figure 8. Food association rules

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift
0	(T, AB)	(W)	0.019531	0.238281	0.011719	0.6	2.518033
1	(W, AB)	(T)	0.019531	0.468750	0.011719	0.6	1.280000

Figure 9. Food association rules

Figure 10 shows a combination of food packages with high support values and menus withlow support in the beverage category. Then in Figure 11 shows a combination of beverage packageswith high support values and menus with low support in the food category.

	antecedents	consequents	Kurang_Laku
0	(B, J)	(N)	Z
1	(J)	(N)	AB
2	(B)	(N)	Y
3	(L)	(N)	AA
4	(G)	(N)	S

Figure 10. Food Package End Result

	antecedents	consequents	Kurang_Laku
0	(T, AB)	(W)	E
1	(W, AB)	(T)	D

Figure 11. Beverage Package End Result

b. Apriori Algorithm

In Figure 12 is the process of finding frequent itemsets in order from the largest support tothe smallest support with a minimum support of 0.1 and in Figure 13 displays the results of a minimum support of 0.01. Minimum support for food and drinks is made different because if the minimum support for food data is 0.01, it will result in 55 association rules. Meanwhile, if the minimum support for beverage data is 0.1, then there are no association rules that qualify.

	support	itemsets
6	0.598558	(N)
1	0.423077	(B)
3	0.346154	(J)
9	0.300481	(N, B)
11	0.259615	(N, J)
4	0.247596	(L)
2	0.218750	(G)

Figure 12. Frequent Itemset Food

	support	itemsets
3	0.468750	(T)
4	0.261719	(U)
6	0.238281	(W)
5	0.156250	(V)
7	0.148438	(X)
2	0.128906	(S)

Figure 13. Frequent Itemset Beverage

Figure 14 is an association rule in the food category with a minimum confidence of 0.6 andproduces 5 rules with an average food lift ratio value of 1.1929. Then in Figure 15 is the associationrule in the food category with a minimum confidence of 0.6 and produces 2 rules with an average lift ratio value of 1.8990.

The reason for using a minimum confidence of 0.6, so that it can use the highest minimum confidence but in the beverage category it can still produce rules.

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift
4	(B, J)	(N)	0.170673	0.598558	0.137019	0.802817	1.341252
2	(J)	(N)	0.346154	0.598558	0.259615	0.750000	1.253012
0	(B)	(N)	0.423077	0.598558	0.300481	0.710227	1.186564
3	(L)	(N)	0.247596	0.598558	0.165865	0.669903	1.119195
1	(G)	(N)	0.218750	0.598558	0.139423	0.637363	1.064831

Figure 14. Food association rules

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift
0	(T, AB)	(W)	0.019531	0.238281	0.011719	0.6	2.518033
1	(W, AB)	(T)	0.019531	0.468750	0.011719	0.6	1.280000

Figure 15. Beverage association rules

Figure 16 shows a combination of food packages with high support values and menus withlow support in the beverage category. Then in Figure 17 shows a combination of beverage packageswith high support values and menus with low support in the food category.

	antecedents	consequents	Kurang_Laku
0	(B, J)	(N)	Z
1	(J)	(N)	AB
2	(B)	(N)	Y
3	(L)	(N)	AA
4	(G)	(N)	S

Figure 16. Food Package End Result

	antecedents	consequents	Kurang_Laku
0	(T, AB)	(W)	E
1	(W, AB)	(T)	D

Figure 17. Beverage Package End Result

Figure 18, Figure 19, and Figure 20 show the runtime results between the apriori algorithmand the fp-growth algorithm. The average result of the 3 experiments is the average runtime using the apriori algorithm 3.178666 seconds while the average runtime using the fp-growth algorithm is3.178666 seconds.

```
Apriori runtime: 4.76837158203125e-07 seconds
FP-Growth runtime: 2.384185791015625e-07 seconds
```

Figure 18 1st Runtime Results

```
Apriori runtime: 2.384185791015625e-07 seconds
FP-Growth runtime: 2.384185791015625e-07 seconds
```

Figure 19 2st Runtime Results

```
Apriori runtime: 2.384185791015625e-07 seconds
FP-Growth runtime: 4.76837158203125e-07 seconds
```

Figure 20 3st Runtime Results

4. CONCLUSION

The application of the Apriori and FP-Growth algorithms in determining food and beverage package menus requires a preprocessing stage to facilitate the modeling process. Following this, modeling is performed using both algorithms based on the minimum support threshold, followed by the search for association rules according to the minimum confidence level. The final step involves combining food menu packages with underperforming beverages, and vice versa.

The results of the study show that the average lift ratio for the food category is 1.1929, while for the beverage category it is 1.8990, with a higher lift ratio indicating a stronger association. A comparison of package results, evaluation using the lift ratio, and runtime between the Apriori and FP-Growth algorithms revealed no significant differences. In the food category, 5 rules were generated, while 2 rules were generated in the beverage category. The most recommended menu packages include: for the food category, combinations of menus J and B with menu N and additional item AA, as well as other combinations; for the beverage category, combinations of menus AB and W with menu T and additional item E, among others.

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