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Comparison of Apriori and Frequent Pattern Growth Algorithm in Predicting The Sales of Goods

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ABSTRACT

The increasing number of bona fide companies, especially in the world of retail minimarkets, PT. Suka Maju innovates to make a company that develops in the retail sector so that it can serve consumers well. With the problems - problems in the company PT. Suka Maju still applies unrelated items so that consumers find it difficult to buy related products. PT. Suka Maju does not apply interrelated items such as coffee and sugar, sauce and noodles, bread and cheese. company PT. Suka Maju must act as quickly as possible and requires data analysis using Market Basket Analysis. The purpose of the existence of data in every transaction of product sales to consumers, data can be processed properly to provide information to companies so that transaction data in every product purchase can be useful and to determine the layout of a product. To deal with this problem, researchers found a pattern that can improve a layout pattern or display of sales items in the retail world, one of which is by utilizing product sales transaction data used to support and find an association rule data mining method technique, comparing the algorithm Apriori and algorithm Frequent Pattern Growth. The purpose of this study is to compare 2 algorithms and choose a better algorithm to help find products that are often purchased together. From the results of the research from 10,005 transactions of 27 attributes using the algorithms Apriori and algorithms Frequent Pattern Growth with the minimum parameters of support = 100, confidence = 100 and lift = 2.58, the algorithm Frequent Pattern Growth has the highest accuracy compared to the algorithm Apriori. In the results of this study, it can be said that the algorithm Frequent Pattern Growth is the best for determining interrelated itemsets.

1. INTRODUCTION

The development of information technology which is currently growing rapidly, it is undeniable that companies in the retail world in particular are competing to keep up with current developments. In this case the company uses technology as well as possible in order to solve problems in the company, especially in the scope of the company and be able to compete with other retail companies.

Suka Maju company is a company in the retail sector, Suka Maju company in Indonesia is growing rapidly and is able to compete with other companies, there are more and more competitors in the retail world. One of the strategies that can be applied by Suka Maju is to provide the best, quality products that suit the daily needs of consumers. Step PT. Suka Maju to serve consumers well by providing quality products to consumers who shop at PT. Suka Maju is in line with the number of enthusiasts who shop at the minimarket to buy basic needs and food, especially for the upper and lower classes so that they can serve well so that consumers who shop at the minimarket can shop again.

The number of problems in the scope of the company is one factor that cannot grow rapidly and can result in the company closing forever, in this era of globalization companies in the retail sector are competing to become the best company, which is able to compete and be able to provide satisfaction to consumers. to shop. [1]

In research conducted by (Bermudez, Apolinario, & Abad, 2016). Building Alfamart stores aims to increase sales sales and generate optimal margins, but a decrease in product sales in a company is undesirable because it will have a negative impact on the company, therefore management must determine a strategic system in the placement of interrelated products, governance The location of the goods on the store shelf is an important key to spending.

The problems experienced by PT. Suka Maju still applies unrelated items so that consumers find it difficult to buy related products. PT. Suka Maju does not apply interrelated items such as coffee and sugar, sauce and noodles, bread and cheese. With this problem, the main objective of this study is to compare the 2 algorithms between the a priori algorithm and the Frequent Pattern Growth algorithm to choose a better algorithm to help find products that are often purchased together such as staples and food.

In determining these steps, the author uses (MBA) Market Basket Analysis as a group of products that are often purchased by consumers in every transaction, the large enough consumer transaction data if processed properly will be more valid. Big data will be processed into valid data so that management can place related products that consumers often buy close together so that consumers can easily find what products consumers buy.

For this reason, in processing data based on the problems above, the author uses the Apriori Algorithm and Frequent Pattern Growth to determine the market basket pattern or commonly referred to as MARKET BASKET ANALYSIS. The data mining function in association rules supports data retrieval of product sales transactions in the field of sales. In the previous results, it was found that there is an a priori algorithm and Frequent Pattern Growth that determines which items are interrelated [8].

2. METHODS

2.1. Research Method

This research method is the use of various ways in obtaining various kinds of data that will be processed and will become more accurate information so that it will be used as the progress of the company. Using this research method is as a basic guideline in conducting research so that the results achieved can be as much as possible from the research objectives. [3]

2.2. Research Steps

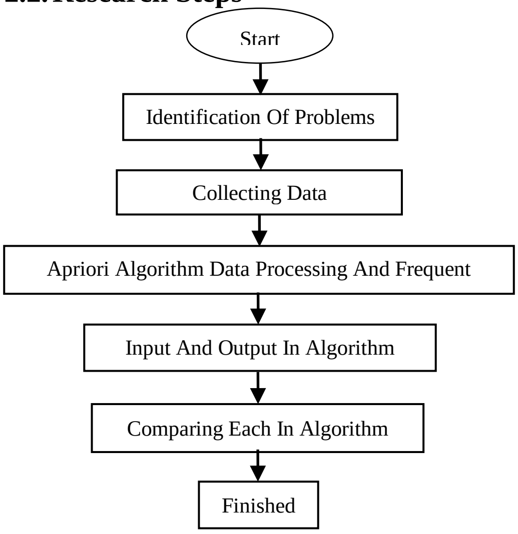


Figure 1. Research Steps

2.3. Problem Identification

Based on the research steps, at this stage is the problem of items that are not related to each other, for example the placement of items is not in the same location so that consumers find it difficult to find related items. Not all stores are related to item placement, there are several stores where the placement of related items is still far apart. This is a factor in the problem, so researchers use data mining with a priori and Frequent Pattern Growth algorithms. [12]

2.4. Collecting Data

Based on the results of interviews with shopkeepers, several questions about the problems experienced can be described : [9]

- Has the customer ever bought a product related to items A and B, but the related products are placed not close together so that consumers find it difficult to find items?
- Has the customer ever bought a product but the desired product is not available?
- How about sales sales every month?

2.5. Data Processing Apriori Algorithm and Frequent Pattern Growth

After collecting data, the next step is to perform data processing, the data is processed based on 10005 transactions of 27 attributes. With the stages of data processing, the data is transformed based on items, examples of brand items that have many variations of names, can be grouped and will become one attribute. [3]

2.6. System Usability Scale

System Usability Scale is to make a user interface (UI) design after the application is finished, the next step is to give a questionnaire to the relevant department in order to provide an assessment of the application that has been made whether the application is good to be declared good or not. The Usability Scale System is a very popular testing system and the Usability Scale system was developed by John Brooke in 1986, the Usability Scale system is put to good use by programmers in various companies [14].

Calculation of the formula to calculate the score of the usability scale system.

$$\bar{x} \quad \frac{x}{n} \tag{1}$$

$\bar{x}$ = average score
$\sum x$ = amount score SUS
n = amount responden

2.7. Conceptual Frameworks

In this research, the process is carried out on a problem within the conceptual framework.

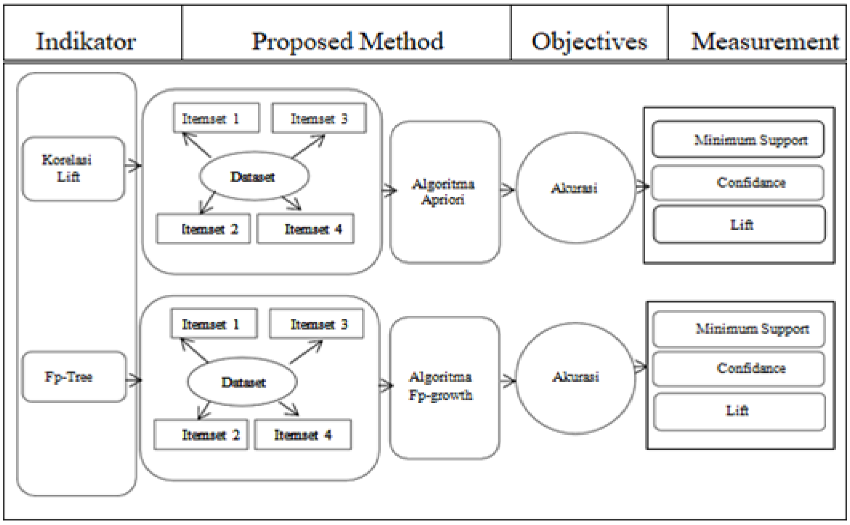


Figure 2. Conceptual Framework

In the conceptual framework above, in this study, the author uses an a priori algorithm (Elevator correlation) and Frequent Pattern Growth (Fp-tree) to approach item sets purchased by consumers simultaneously. For a priori algorithm (Elevator correlation) uses 4 item sets and searches for frequent item sets based on the k-item set and to measure valid or not filed data in a dataset and for accuracy results, accuracy and precision can be measured with minimum support, confidence and Lift values. For the Frequent Pattern Growth algorithm (Fp-tree) using 4 item sets, to look for data sets that often appear on each item and will form accuracy and the results will form drinking support, confidence and lift values. [11].

2.8. Hypothesis

Based on the formulation of the problem that has been described, the research hypothesis is as follows:

It is assumed that the identification of interrelated goods in a minimarket using Frequent Pattern Growth will be better than a priori.

3. RESULTS AND DISCUSSION

3.1. Sampling method

In this study, the sample used is product sales data at a minimarket in 2020 with the sample selection method, researchers collect information by conducting interviews, observations, and questionnaires.

3.2. Secondary Data Collection Method

The data used in this study is using the Product Sales database from January 2020 to December 2020. The data collected is Product Sales Transactions. The following is an example of the Product Sales database obtained.

Table 1. Product Sales Transaction

KODE_TOKO	TGL_TRS	ITEM CODE	NOMER TRANSAKSI	TRANSACTION NUMBER	PRICE	TRANSACTION HOURS	DESCP
XXXX	7/1/2020	101642	1	1	3800	8:20:35	NPL AIR PET 600ML
XXXX	7/21/2020	109497	1	1	6800	22:12:57	POCARI PET SWEAT 350ML
XXXX	6/4/2020	125034	1	1	6200	8:20:35	AQUA AIR CLICK&GO PET 750ML
XXXX	9/8/2020	194695	1	1	15500	6:50:10	SARI BREAD TRY CKT SRKAYA 214G
XXXX	1/4/2020	196009	1	1	9300	8:20:35	BEAR BRAND ORI CAN 189ML
XXXX	7/4/2020	414150	1	1	27400	8:20:35	ESSE CHANGE JUICY 20
XXXX	12/8/2020	5868	2	2	7600	6:52:30	AQUA AIR PET 600ML
XXXX	7/8/2020	120163	2	1	7000	6:52:30	RTD HOT CAPPUCINO
XXXX	11/8/2020	125134	2	1	3900	6:52:30	PUCUK HARUM LESS SUGAR PET350ML
XXXX	7/10/2020	5867	3	2	12400	6:55:05	AQUA AIR PET 1500ML
XXXX	2/18/2020	5868	3	1	3800	23:02:06	AQUA AIR PET 600ML
XXXX	3/8/2020	5868	3	2	7600	6:55:05	AQUA AIR PET 600ML

Table 1 is following data is based on product sales transaction data for each consumer purchased for daily needs.

Table 3.2 Data Attribute Description

KD_STORE	KD_STORE
TGL_TRS	TRANSACTION DATE
PLU	ITEM CODE
NO_BON	TRANSACTION NUMBER
JUMLAH_QTY	QUANTITY
PRICE	PRODUCT PRICE
JAM_TRANS	SALES TRANSACTION HOURS
DESCP	GOODS PRODUCT

Table 2 is based on the fields and contains the meaning of each.

Table 3 Sales transaction data processing

NO_BON	MILK	BISCUITS	MINERAL WATER	SUGAR	BABY DIAPERS	CLEANER	CHOCO LATE	CANDY	NOODLES	SAUCE	SOY SAUCE	BREAD	CHEESE	CIKI
1	1	1	1	0	0	0	0	1	1	0	0	1	0	1
2	1	1	1	0	0	0	1	1	1	0	1	1	0	1
3	1	1	1	0	1	0	1	1	1	1	0	1	0	0
4	1	1	1	0	0	0	1	1	0	1	1	1	0	1
5	0	0	1	1	0	0	1	1	1	0	0	1	0	1
6	1	0	1	0	1	0	0	1	1	0	1	1	0	1
7	0	1	1	1	1	0	0	1	0	0	0	1	0	1
8	1	1	1	1	0	0	1	1	0	1	0	1	0	1
9	1	0	1	0	0	1	1	1	1	1	0	1	0	1
10.000	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10.001	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10.002	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10.003	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10.004	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10.005	1	0	0	0	0	0	0	0	0	0	0	0	0	0

NO_BON	COOKING OIL	TEA	COFFEE	BUTTER	TOOTHPASTE	TOOTHACHE	SOAP	SHAMPOO	PERFUME	CLOTHING DETERGENT	INSECT REPELLENT	DRUG	HANDBODY
1	0	1	1	0	0	0	0	1	0	0	0	1	1
2	0	0	1	0	1	0	1	0	0	1	0	1	1
3	0	1	1	0	1	1	0	0	0	0	0	1	1
4	0	1	1	0	1	1	1	1	0	0	0	1	1
5	0	1	1	0	0	0	0	0	0	0	0	1	1
6	1	1	1	0	1	0	1	0	1	1	0	1	1
7	0	1	1	0	1	0	0	0	0	0	1	1	0
8	1	1	1	0	0	1	0	0	0	0	0	1	1
9	1	1	1	0	1	1	0	1	0	0	0	1	1
10.000	0	0	0	0	0	0	0	0	0	0	0	0	0
10.001	0	0	0	0	0	0	0	0	0	0	0	0	0
10.002	0	0	0	0	0	0	0	0	0	0	0	0	0
10.003	0	0	0	0	0	0	0	0	0	0	0	0	0
10.004	0	0	0	0	0	0	0	0	0	0	0	0	0
10.005	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3 shows the attribute data selected based on the items, they are marked with the letters 1 and 0. If 1 indicates the items purchased by consumers and 0 indicates the items are not purchased by consumers. After the attribute is selected based on the next step, the attribute data will be uploaded into WEKA 3.8 which will determine the results of support and confidence.

Table 4 Attributes Of Biscuits

NO_BON	DESCP
26	ROMA MALKIST CHEESE MNS 105/120G
114	ROMA MALKIST CRACKERS 135G
118	ROMA MALKIST CHOCOLATE 105/120G
120	ROMA COCONUT CREAM 180G
147	ROMA MALKIST CHEESE TOWER 165G
159	ROMA SW CHOCOLATE 216G
195	ROMA MALKIST CPCN / TRMS 115G
255	ROMA WFR SUPERSTAR SNAPS 28G
280	ROMA COCONUT BISC 300G
280	ROMA COCONUT BISC 300G
294	ROMA COCONUT CREAM 180G
305	ROMA SW CHOCOLATE 216G
314	ROMA MALKIST CHOCOLATE 105/120G
348	ROMA WAFELLO CARAMEL 130G
354	ROMA MALKIST COCONUT CHOCOLATE135G

Table 5 Attributes Sugar

NO_BON	DESCP
10	SILVER QUEEN NUT 65G
24	SILVER QUEEN BITES CASHEW 40G
73	SILVER QUEEN CHUNKY CASHEW 100G
136	SILVER QUEEN NUT 65G
190	SILVER QUEEN ALMOND 65G
190	SILVER QUEEN CHUNKY CASHEW 100G
190	SILVER QUEEN FRUIT&NUT 65G
271	SILVER QUEEN BITES CASHEW 40G
274	SILVER QUEEN CHUNKY CASHEW 33G
294	SILVER QUEEN CHUNKY CASHEW 33G
297	SILVER QUEEN CHUNKY CASHEW 33G
449	SILVER QUEEN ALMOND 65G
451	SILVER QUEEN CHUNKY CASHEW 100G
459	SILVER QUEEN CHUNKY CASHEW 33G
480	SILVER QUEEN CHUNKY WHITE 100G
511	SILVER QUEEN NUT 65G

Table 6 Attributes Sugar Mineral water

NO_BON	DESCP
5	AQUA AIR PET 1500ML
9	AQUA AIR PET 600ML
14	AQUA AIR PET 600ML
15	AQUA AIR PET 1500ML
15	AQUA AIR PET 600ML
21	AQUA AIR PET 1500ML
25	AQUA AIR PET 600ML
26	AQUA AIR PET 1500ML
27	AQUA AIR PET 600ML
29	AQUA AIR PET 600ML
30	AQUA AIR PET 600ML
33	AQUA AIR PET 600ML
34	AQUA AIR PET 1500ML
34	AQUA AIR PET 600ML
35	AQUA AIR PET 1500ML
37	AQUA AIR CLICK&GO PET 750ML
38	AQUA AIR PET 600ML

Based on table 3.4, table 3.5, table 3.6 and others will be used as attributes based on sales transaction data and then selected items that match the product naming of each itemset to be processed based on the invoice number and product naming purchased simultaneously by consumers**.**

3.3. Market Basket Analysis

Market Basket Analysis is a method used in marketing strategies, the data used in sales transactions to consumers is carried out every day as long as the sales transaction process to consumers continues. Method Market Basket Analysis on consumer behavior from a certain group, consumers who shop at minimarkets become a factor in the relationship between sales transactions that are placed in the market basket with purchases. [4] Data mining is an automatic search process and useful information in storing large data, data mining is also called an observational data analysis process to determine unexpected data from a group that can summarize it into valuable information. Data mining using static techniques, mathematics, artificial intelligence. [5]

3.4. Apriori Algorithm

The algorithm apriori aims to find the results of frequent item sets that often appear in every data on sales transactions purchased by consumers. The number of customers buying a product at the minimarket is one of the factors causing the search for a number of item sets, the large number of sales transaction data is one of the item sets that must be processed in order to produce minimum support and confidence in the data. The number of combination items is a problem factor, to find solutions to the causes of the large number of data item combinations can reduce the number of candidate item sets. [6]

- Support: Every transaction data on the purchase of product sales purchased by consumers who shop at minimarkets buy items A and B simultaneously
  Support formula:

$$\text{Support A} = \frac{\text{The number of transactions contains A and B}}{\text{Amount of transactions}} \quad (1)$$

- Confidance: Consumers buy product A, of course, consumers buy B simultaneously in one transaction. Then the if X then Y rule is m/n.
  Confidance formula:

$$\text{Confidance A} = \frac{\text{The number of transactions contains A and B}}{\text{Number of transactions A}} \quad (2)$$

3.5. Lift ratio

Lift ratio is a measure to form association rules, the validity or invalidity of a data will be seen as the lift ratio value. [7] To measure the validity or invalidity of a data using the lift ratio. Lift ratio is a measuring tool to determine the association rules where the lift value > 1 then the data is declared valid so that the lift ratio value is getting stronger [3]

$$\text{Lift Ratio} = \frac{\text{Support } (A \cap B)}{\textit{Support (A)x Support B}} \quad (3)$$

3.6. Association Rules

Association rules aim to find related items in a database, these rules can be used for related products in product sales transactions. The association rules method is known as model market analysis Associative. The rules of this method can meet the supporting value and the level of confidence that are carried out simultaneously. Candidate for obtaining results from the frequent item's set. This generate candidate only done be with apriori algorithm, the Frequent Pattern Growth algorithm does not's have candidate generation. To find item sets in the Frequent Pattern Growth algorithm, only use Frequent Pattern-tree which is called a series of trees. The apriori algorithm perform the scanning process of the dataset repeatedly the while Frequent Pattern Growth algorithm carried out only once, this cause the Frequent Pattern Growth algorithm to be superior apriori algorithm. [4]

To see what items are often purchased by consumers at the same time in the market basket, this association rule has "if-then." "if. then.." can be used as a function of association [8]

$$\text{Rule: } x \rightarrow y \begin{cases} Support = \dfrac{frq(X.Y)}{\text{N}} \\ Confidence = \dfrac{frq(X.Y)}{frq(X)} \end{cases} \quad (4)$$

3.6. Frequent Pattern Growth Algorithm

As the algorithm develops, scientists develop an apriori algorithm with the Frequent Pattern Growth algorithm. To get results from the apriori algorithm, it is very necessary to generate candidates to get the results from the frequent item set. This generate candidate can only be done with the a priori algorithm, Frequent Pattern Growth algorithm does not have a generated candidate. [9]

3.7. Frequent Pattern Tree

Frequent Pattern tree is used as a data store based on the item set. In building the item set, the item set must determine the transaction data in each item based on the fp-tree. [4] A collection of data from each sales transaction has the same item set, the same item set can be grouped based on many transaction data, the more structured the data results will be. The advantage of fp-tree that it only be processed with two data transfers, Fp-tree is called the fp-tree framework, it also has a very good data structure to form frequent patterns. [10]

3.8. Input And Output In Algorithm

After the data has been processed, the next step is to perform input and output. Before being tested into the system, the data is input and output using the weka tools so that the resulting data can be better which of the apriori and Frequent Pattern Growth algorithms. After finding most accurate result of the two algorithms.

3.9. The Comparing Results Each Algorithm

To compare the results of apriori and Frequent Pattern Growth algorithms, you will get results of supporting and confidence. The method of developing the a priori and Frequent Pattern Growth algorithms is to find the best accuracy results. [13]

3.9.1. Apriori Algorithm

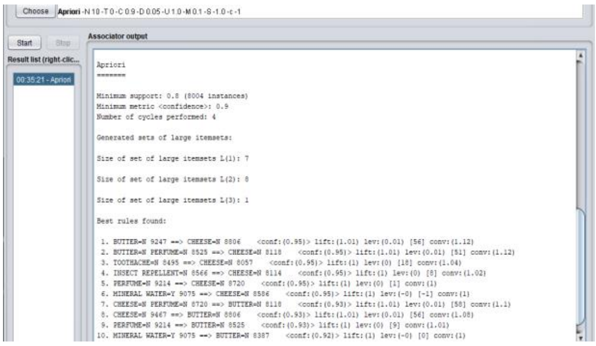


Figure 3. Apriori Algorithm Test Results

Based on transaction data of 10.005 transactions and 27 attributes, the results of the Apriori Algorithm testing using the weka tools. Minimum support 0.8 and confidence 0.9. For the accuracy of the accuracy on interrelated items is not significant.

1. BUTTER=N 9247 ==> CHEESE=N 8806 < conf: (0.95) > lift: (1.01) lev: (0.01) [56] conv: (1.12)
2. BUTTER=N PARFUME=N 8525 ==> CHEESE=N 8118 < conf:(0.95) > lift: (1.01) lev: (0.01) [51] conv:(1.12)
3. TOOTHACHE =N 8495 ==> CHEESE=N 8057 < conf: (0.95) > lift: (1) lev: (0) [18] conv: (1.04)
4. REPELLENT INSECT =N 8566 ==> CEHEESE=N 8114 < conf: (0.95) > lift: (1) lev: (0) [8] conv: (1.02)
5. PARFUME=N 9214 ==> CHEESE=N 8720 < conf: (0.95) > lift: (1) lev: (0) [1] conv:(1)
6. MINERAL WATER=Y 9075 ==> CHEESE=N 8586 < conf: (0.95) > lift: (1) lev: (-0) [-1] conv: (1)
7. CHEESE=N PARFUME=N 8720 ==> BUTTER=N 8118 < conf: (0.93) > lift: (1.01) lev: (0.01) [58] conv: (1.1)
8. CHEESE=N 9467 ==> BUTTER=N 8806 < conf: (0.93) > lift: (1.01) lev: (0.01) [56] conv: (1.08)
9. PARFUME=N 9214 ==> BUTTER=N 8525 < conf: (0.93) > lift: (1) lev: (0) [9] conv: (1.01)
10. MINERAL WATER=Y 9075 ==> BUTTER=N 838 < conf: (0.92) > lift: (1) lev: (-0) [0] conv: (1)

3.10. Frequent Pattern Growth Algorithm

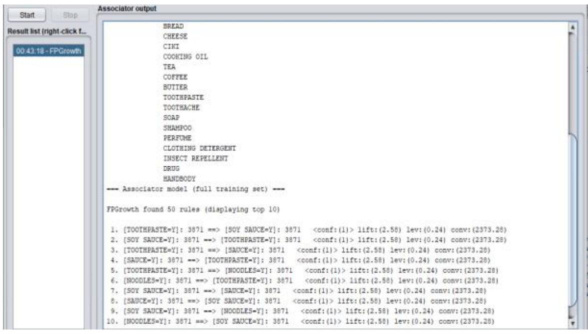


Figure 4. Frequent Pattern Growth Algorithm Testing Results

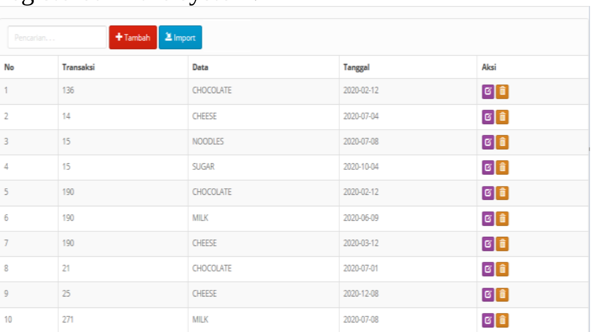
By using transaction data 10.005 and 27 attributes, the results of Frequent Pattern Growth algorithm with minimum supporting 100 dataset and confidence 100 dataset, the Frequent Pattern Growth algorithm has a very accurate level of accuracy in this case the comparison of the apriori and Frequent Pattern Growth algorithms for an accurate level of accuracy is the Frequent Pattern Growth algorithm.

1. [SAUCE =Y]: 3871 ==> [TOOTHPASTE =Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)
2. [TOOTHPASTE=Y]: 3871 ==> [SAUCE=Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)
3. [SAUCE =Y]: 3871 ==> [NOODLES=Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)
4. [NOODLES=Y]: 3871 ==> [SAUCE=Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)

5. [SAUCE=Y]: 3871 ==> [SOY SAUCE=Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)
6. [SOY SAUCE =Y]: 3871 ==> [SAUCE=Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)
7. [TOOTHPASTE=Y]: 3871 ==> [Noodles =Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)
8. [NOODLES=Y]: 3871 ==> [ODOL=Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)
9. [TOOTHPASTE=Y]: 3871 ==> [SOY SAUCE =Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)
10. [SOY SAUCE=Y]: 3871 ==> [TOOTHPASTE =Y]: 3871 < conf: (1) > lift: (2.58) lev: (0.24) conv: (2373.28)

Figure 5. Main Course

The main menu can be accessed when the user inputs the username and password that has been registered in the system.



No	Transaksi	Data	Tanggal	Aksi
1	136	CHOCOLATE	2020-02-12	
2	14	CHEESE	2020-07-04	
3	15	NOODLES	2020-07-08	
4	15	SUGAR	2020-10-04	
5	190	CHOCOLATE	2020-02-12	
6	190	MILK	2020-06-09	
7	190	CHEESE	2020-03-12	
8	21	CHOCOLATE	2020-07-01	
9	25	CHEESE	2020-12-08	
10	271	MILK	2020-07-08	

Figure 6. Import Data

The data menu can be used by the user to process data to determine the results of support and confidence. Before determining the results, the user can import data, add, delete.

Show 10 entries Search:

No	Rule	Support	Confident	Fp-tree
1	CHOCOLATE => CHEESE	4334.6073662266%	8030.254264564%	1.0979131484
2	MILK => CHOCOLATE	4334.6073662266%	29631.828978622%	1.0979131484
3	CHEESE => CHOCOLATE	2666.7824878388%	18230.403800475%	0.7631578493
4	CLEANER => INSECT REPELLENT	2692.8422515636%	10638.29787234%	1.4544903219

Showing 1 to 10 of 21 entries Previous 1 2 3 Next

Figure 7. Frequent Pattern Growth Result

The Results menu can be seen. After the user determines the support and confidence, the results of related items can be seen.

Questions from System Usability Scale *(SUS)*.

1. Has this application been used in other companies
2. Does this application have a lot of errors
3. This is application easy to use
4. Who has the right to process this application
5. How much data can be uploaded
6. How technical using in application
7. I am feel there is a discrepancy in this application
8. I am feel this application well running
9. I am need good understanding with this app
10. I am need to do with trial first

Table 7. Opinion of System Usability Scale *(SUS)*

Answer	Score
Agree strongly	1
Agree	2
Disagree strongly	3
Do not agree	4
Doubtful	5
No response	6

Each employee is required to fill out a questionnaire and must be based on the existing questions. After filling out the questionnaire, the next step is to calculate the System Usability Scale *(SUS)*. [14]

Table 8. System Usability Scale Question Results *(SUS)*

Respondent	SUS Question										Result
	1	2	3	4	5	6	7	8	9	10	
Andi	5	1	1	1	3	1	1	1	5	1	95
Meta	5	1	1	1	1	1	6	1	5	1	78
Rudi	5	4	6	1	3	1	2	3	3	1	63
Doni	1	4	5	1	4	1	1	1	3	1	65
Apri	1	1	2	1	4	2	2	1	4	1	78
Mei	1	1	3	2	5	1	1	1	3	1	78
Juna	1	1	1	2	5	2	1	3	4	1	78
Rudi	1	4	4	2	5	1	6	1	4	1	58
Tomi	1	1	6	2	6	2	6	1	4	1	60
Doni	1	4	4	2	4	2	6	3	3	1	45
Average											695/10=69

From the results of System Usability Scale (SUS) questions obtained based the respondents' assessments in form of questions, see table 4,164 of 10 respondents and will form a result of 695 and divided into 10 results 69. [14]

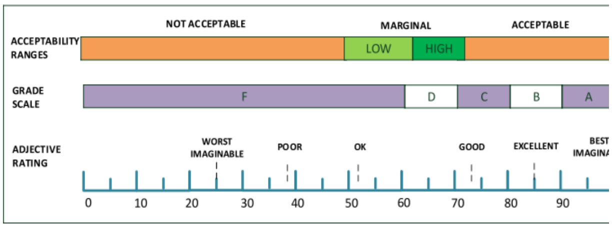


Figure 8. Determination of Assessment Results (Bangor, Kortum, & Miller, 2009)

See determination A = worst imaginable, B = poor, C = okay, D = good, E = excellent and F = best imaginable. For the percentile (percentiles rank) of the title prediction of the comparison goods sales using the apriori and Frequent Pattern Growth algorithm, this is obtained with a result score of 69 which is ranked C (ok) with this for the application made by the author it is still feasible to be implemented by the company. [15]

4. CONCLUSION

By applying the concept of the Internet of Things at The results of the implementation of tools and tests carried out on electronic devices and applications. First shows NodeMCU working and in sync with gadget devices via ping data. Electronic devices and applications run well with appropriate response. Meanwhile, testing on the Google Assistant voice command also worked well. The tool can work well to support the development of human activities in using sound responses to turn on the lights.

The ease with which users can use technology to help turn on lights, fans and enable other household electrical devices to work with less energy. Homeowners who find it difficult to take care of many members at the same time need better performance with technology being very helpful.home, the house can be controlled by electrical or electronic devices rarely remotely through networks such as routers and hotspots. The design of this electrical control device uses the NodeMCU as the main system which is programmed to control electrical devices via an Android smartphone in a manner such as Google Assistant which is instructed to turn on and turn off electrical appliances at home. No need to use a lot of energy just by controlling electrical devices on the Android application makes work at home efficiency.

The challenge in operating electronic devices such as lights is actually not too difficult, but in the current era, improvements need to be made with smart home technology that is integrated with full security so that it becomes a technology unit that can be controlled remotely and has real-time data.

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