

A Data Mining Approach For Product Promotion and Inventory Solution using FP-Growth Algorithm

Hartono
Faculty of Computer Science
Universitas Mercu Buana
Jakarta, Indonesia

Devi Fitriannah
Faculty of Computer Science
Universitas Mercu Buana
Jakarta, Indonesia

ABSTRACT

This study aims to find interesting patterns on the database transaction so that it can be used as a recommendation sales promotion and inventory product. Companies have difficulty finding interesting transaction patterns in large databases, so it will be difficult to determine the right product promotions and inventory. To resolve these problems are to use data mining techniques with association rule. In previous studies, most studies adopt Apriori algorithm to analyze the association rules. In this study, the data mining technique used is the association rules algorithm FP-Growth. In the FP-Growth algorithm did generate candidates as in Apriori algorithm and using a development concept Tree in frequent itemset search so that it requires faster than Apriori. Some of the analyzes produced in this study are higher minimum support values and minimum trust used will result in fewer items and association rules. Association rule in this study has a lift ratio value of more than 1.00, meaning that item K and L are actually bought together. The higher the lift ratio produced shows the stronger the association rules are formed. The results of this study are the minimum confidence of 97.63%, the maximum trust is 99.37% and the lift ratio is 1,00013798. These results can be used as recommendations for optimizing product promotions and inventory.

General Terms

Data Mining; Database; Fp-Growth; Association Rule; Algorithm

Keywords

Promotion, Knowledge Discovery Database Data Mining, Association Rule, Fp-Growth, frequent itemset.

1. INTRODUCTION

Trading business is one of the businesses selling various types of human goods in retail. Trading business competition is very tight so that appropriate market strategy are needed to support the increase in transaction value [1] and company profits. The good market strategy can be obtained by knowing the relationship between items purchased by customers, so it is necessary to do research and analysis of the database. This research was conducted with the aim to determine the pattern or relationship between the purchase of an item whether related and influence other items. Companies find it difficult to find interesting patterns of transactions in large database of sales transactions. So that it will have difficulty also in determining the right promotions and product inventory. The solutions to find interesting transaction patterns is to use Data Mining techniques. Data mining technique known as Knowledge Discovery in Database (KDD) is a method used in the analysis of large database observations to find interesting patterns of relationships of a transaction [2]. The pattern is then identified to determine the relationship between items

and to determine the items most often purchased simultaneously using the Association rule method [2]. Previous research, most of the studies adopted the Apriori algorithm in analyzing association rule. In this study the data mining technique used is the association rule with the FP-Growth algorithm. The FP-Growth algorithm does not generate generate candidates as in the Apriori algorithm and uses the concept of Tree development in searching for Frequent Itemset [3] so it requires faster compared to Apriori. FP-Growth is a precise and fast algorithm for processing large amounts of data [4][5][6]. Some of the analyzes produced in this study are that the higher the minimum support and minimum confidence values used will result in fewer itemset and association rules. The association rules in this study has a lift ratio value of more than 1.00, meaning that item K and L are actually bought together. The results of this study are the minimum confidence of 97.63%, the maximum trust is 99.37% and the lift ratio is 1,00013798. These results can be used as recommendations for optimizing product promotions and inventory so as to increase profits for the company.

The purpose of this study is:

1. Exploring hidden information from the database that can be a recommendation in making decisions to determine market strategies.
2. Presenting the association of items that are often purchased by customers so that they can be used to determine the right product promotion.
3. Presenting the fewest and most sold items in the dataset so that it can be used in managing inventory.

2. LITERATURE REVIEW

2.1 Related Research

The study was conducted referring to previous studies:

- a. "Analisa Pola Belanja Menggunakan algorithm FP-Growth, Self Organizing Map (SOM) dan K Medoids" [7]. This research is about FP-Growth that is used to analyze items purchased simultaneously. Accurate results obtained from this study can be measured using a lift ratio. The Lift ratio shows a valid value in the transaction process that provides information on whether item A was purchased together with item B. A transaction is said to be valid if it has a lift ratio value of more than 1, is that in the transaction, item A and B purchased simultaneously.
- b. "Implementasi Algoritma FP-Growth Menggunakan Association Rule Pada Market Basket Analysis" [4]. With the results of the FP-Growth algorithm is more efficient in processing basket market or consumer shopping basket data, using the association rule can find

out shopping rules consumers such as the relationships of each product purchased by consumers and affect the types of consumers with the products purchased and association rule can provide management decisions for product displays, promotions, marketing strategies.

2.2 Association Rule

Association rule mining is useful for discovering interesting relationships hidden in large data sets [8]. Association rules is data mining processes to find and determine all relationships between items in a database that meet minimum supports and minimum confidence [2]. Association rule is one method that aims to find patterns that often occur among many transactions, where each transaction consists of several items. In determining a relationship, there is interesting measure, that is:

- (1) Support: support is a parameter that indicates the level of dominance of an item (item or itemset) over the whole transaction [9][10]. This measure is then used to determine whether an item or itemset meets the requirements in confidence.
- (2) Confidence: confidence is a measure that shows the relationship between two items or items conditionally. Example, if confidence K and L are worth 1 (100%), then it can be concluded that if the customer buys K definitely buy L. However, if the value of confidence is only close to 1 (eg 0.8), the conclusion is that if the customer buys the K item, it tends to buy L [7].

The support value for item K can be found by the following equation:

$$Support(K) = \frac{Number\ of\ transactions\ containing\ K}{Total\ transaction} [1]$$

And to get the minimum value of support for two items can be found with the following equation:

$$Support(K, L) = \frac{Number\ of\ transactions\ containing\ K\ and\ L}{Total\ transaction} [2]$$

After all patterns high frequency is found, then the rules are sought associative that meets the minimum requirements for confidence by calculating the confidence of associative rules $K \rightarrow L$. Score confidence from the rules $K \rightarrow L$ is obtained from the equation:

$$Confidence(K \rightarrow L) = \frac{Number\ of\ transactions\ containing\ K\ and\ L}{Number\ of\ transactions\ containing\ K} [11]$$

2.3 FP-Growth

This study uses a large database so that the FP-Growth algorithm is very appropriate to be used in this study. FP-Growth algorithm is an alternative algorithm that is quite effective against finding the most common dataset (frequent itemset) in a large dataset [12][13][14]. The FP-Growth algorithm process only mapping data or scans the database twice to build a "tree" structure so that it is also known as the FP-Tree algorithm [5]. Using the FP-Tree structure, the FP-Growth algorithm can directly extract frequent itemset from the FP-Tree arrangement that has been formed [15]. The FP-Growth algorithm is divided into three main steps: generation of Conditional Pattern Base, FP-tree conditional generation and frequent itemset search [2].

3. METHODOLOGY

The research methodology goes through the steps shown in Figure 1 below.

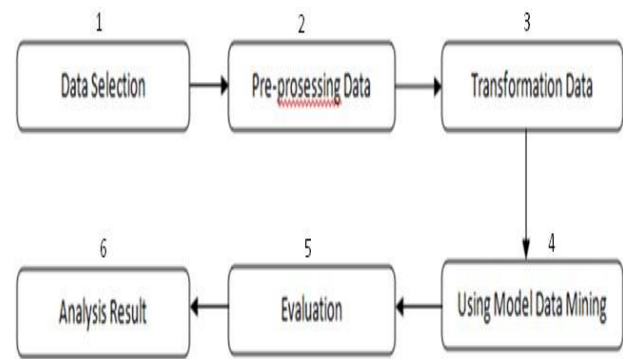


Fig 1: Proposed

3.1 Data Collection

In this process the selection of dataset in a database is then selected the target dataset, entities or attributes that will be processed for research. The results of the data selection are then paired in a file or an entity that is different from the operational database [16][17]. This study the data used transaction data from 2016 to 2018 with 2,534,033 rows of data.

Table 1. Data Selection Sample

Attibut	Description	Data Type	Data
1	Transaction_number	Char	003133-30042015-0026
2	Seq	Char	1
3	PLU	Char	8232653289675
4	Item_Description	Varchar	CHOCO/BRA, 9,L
5	Qty	Decimal	1
6	Price	Money	249000
7	Customer_ID	Char	476448
8	Spending_Program_Id	Char	2
9	Transaction_Time	Char	1
10	CardNo	Char	8091200016076900
11	Card_Name	Varchar	HERI SUSANTO

12	Class	Char	UCL
13	DP2	Char	LD
14	Description	Char	CHOCO/BRA, 9,L
15	Brand	Varchar	UNDERCOLORS

3.2 Preprocessing Data

This process is carried out by the integration of several entities that constitute data that will be carried out research. Integration makes data simpler and can be adjusted to the

required attributes. This step is also carried out checking inconsistent data, data noise, duplicate data and correcting data errors without changing the data contents [6]. After integrating data into 1005232 rows.

Table 2. Example of Dataset

No	Cust_Id	Date	Qty	Amount	Class
1	CUST_1	17012016	1	480000	BON
2	CUST_1	17012016	1	188000	QBY
3	CUST_1	30012016	1	465000	PYO
...
1005230	CUST_221468	30102017	1	799000	ANV
1005231	CUST_221469	22042017	2	885000	CLQ
1005232	CUST_221469	22042017	2	1200000	UDC

Table 2, contains the customer id, date of purchase, number of items purchased, total purchases and class or brand of items purchased. Based on Table 2, it can be seen that customers buy several classes or brands of items and at different time.

3.3 Transformation Data

This process changes or transforms data from the initial data into data following the format of the data mining process [18] without changing the contents of the data [15][19]. In this stage the process of summarizing (aggregation), pivoting and changing numeric types to the binominal.

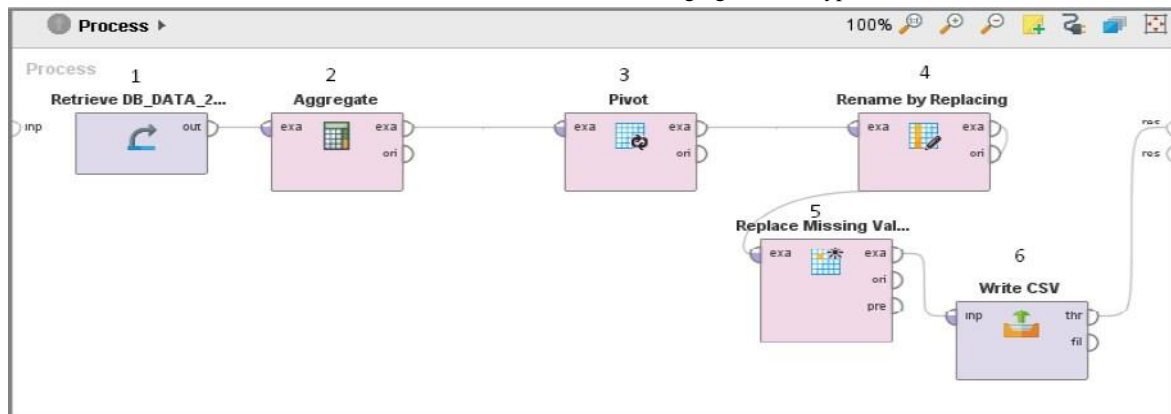


Fig 2: Transformation Data

In Figure 2, it can see the data transformation process with several sub processes are aggregate, pivot, rename and replacing and replace missing value. A more detailed process description can be seen below.

- ❖ Operator No.1: The process of retrieving data to be processed, the data can be in the form of extension excel files, CSV (Comma-Separated Values) files and can be SQL Server database. The next data will be processed by the next operator. This operator can be used to access the repository.
- ❖ Operator No.2: Aggregate is a process used to produce value by classifying the same value by determining certain criteria. Many aggregation functions including

SUM, COUNT, MIN, MAX, AVERAGE, and many other similar functions.

- ❖ Operator No.3: The Pivot operator rotates the Dataset from row to column and vice versa by grouping several attribute values from the same group into one value and summarizing the data in various calculations (sum, average, and others).
- ❖ Operator No.4: This operator can be used to replace the name of a set of attributes by replacing part of the attribute name with the specified replacement.
- ❖ Operator No.5: This operator replaces the Missing value in the selected attribute example with the specified

replacement. Missing values can be replaced by Zero, minimum, maximum or average values of that attribute.

❖ Operator No.6: This operator is used to write or save CSV (Comma-Separated Values) files.

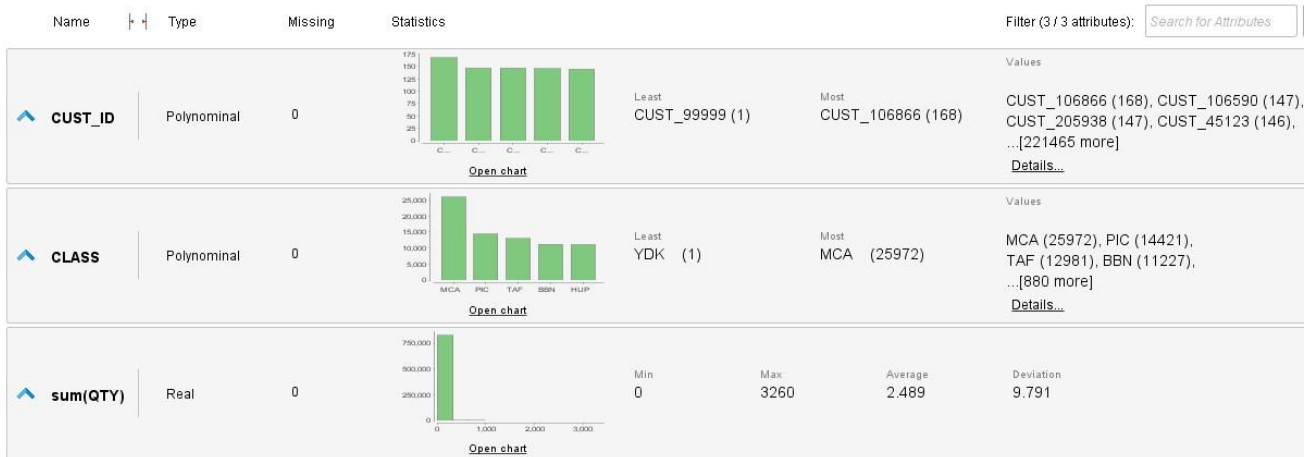


Fig 3: Result Aggregate

In Figure 3, it can see the results of the aggregate process, these results show the class or brand that is most sold and customers who often shop. The data can be used to manage

inventory items and to find out loyal customers so they can personally promote the product.

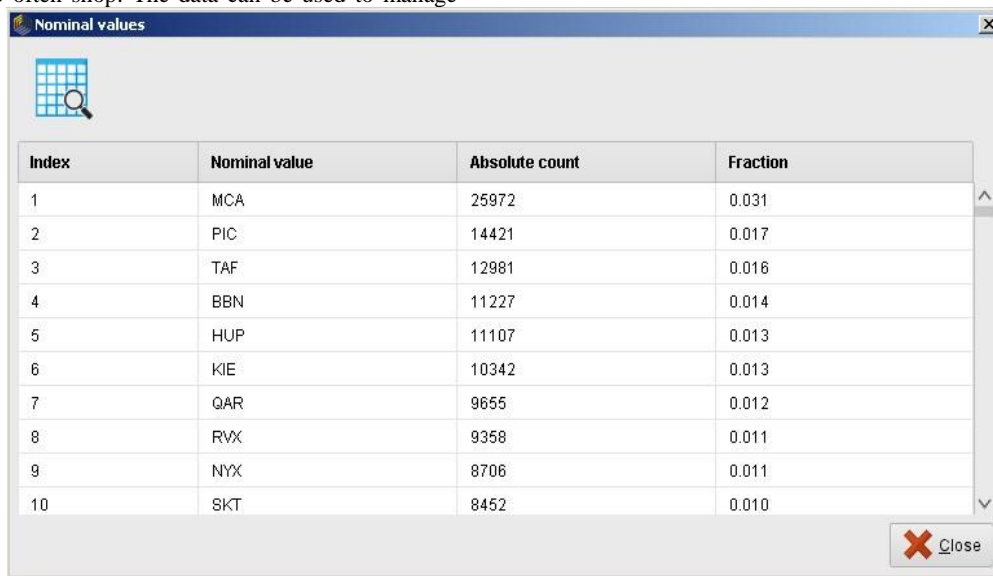


Fig 4: Best-Selling Item

Base on Figure 4, shows the best-selling items as inventory management recommendations so that the company will provide good inventory to meet customer needs and will not

store unsold goods. For example, sales in the 2016- 2018 MCA sold 25,972 items and were the most sold items.

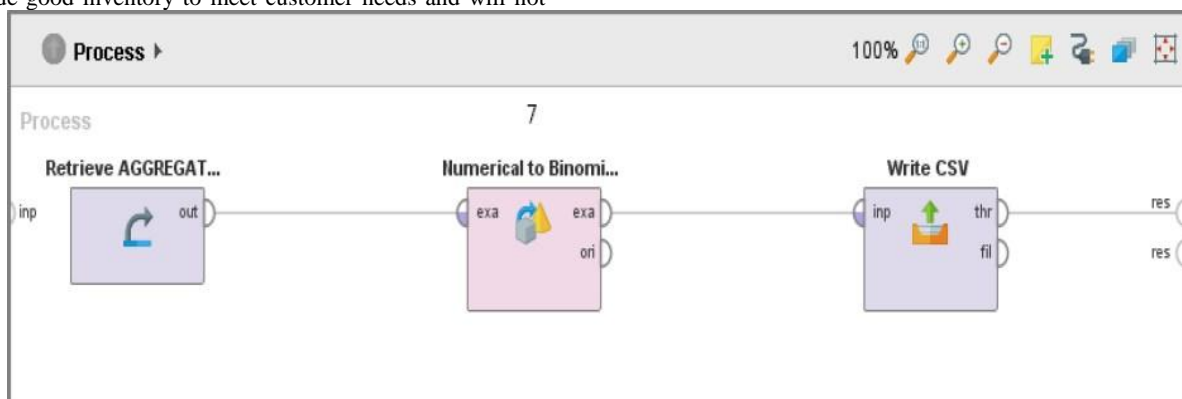


Fig 5: Numerical to Binominal

Figure 5, shows the numerical to binominal process with the aim that the data can be processed using the FP-Growth algorithm. Detail Process as described below.

- ❖ Operator No.7: The Numeric Operator to Binominal changes the numeric attribute type to a binominal type (also called binary). This operator not only changes the selected attribute type but also maps all the values of this attribute to the corresponding binominal values. The binominal attribute can only have two possible values which are 'true' or 'false'. If the attribute value is between the minimum and maximum values specified, it becomes

'false', otherwise 'true'. The minimum and maximum values can be determined by the min and max parameters respectively. If the value is lost, the new value will be lost. The default limits are both set to 0.0 so that only 0.0 is mapped to 'false' and all other values are mapped to 'true' by default.

3.4 Model Data Mining

Data that has been through the process of data selection, preprocessing and transformation, then the data will be processed using RapidMiner. The steps for processing association rules are shown below.

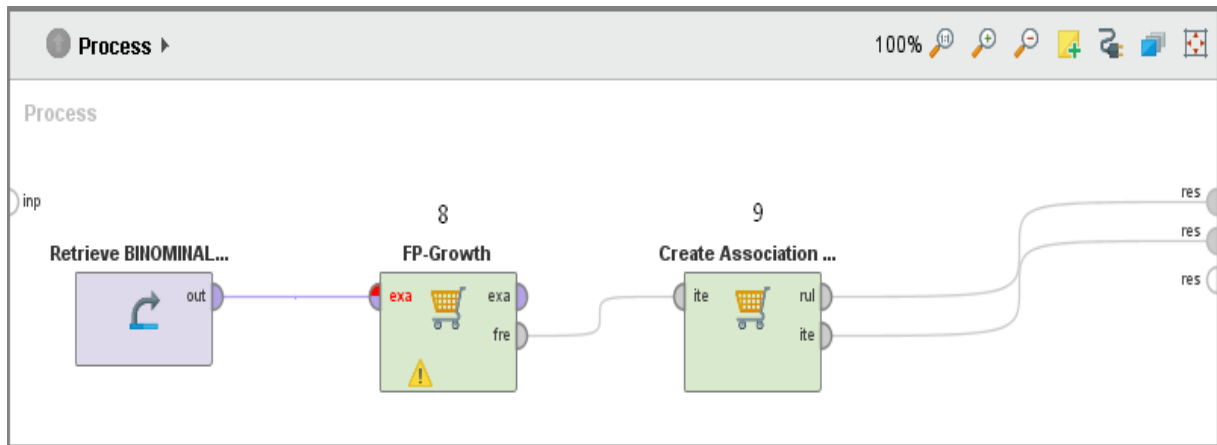


Fig 6: Data Mining Model

In figure 6, shows the data mining process model using the FP-Growth algorithm. The process can run if the data has gone through the preprocessing process in Figure 2 and transformation in Figure 5. More detailed information on the information below.

- ❖ Operator No.8: This operator efficiently calculates all sets of items that often arise from a given dataset using the FP-tree data structure. This operator can run if all the values in the attribute are of type binominal.
- ❖ Operator No.9: This operator generates a set of association rules from the set of items that appear frequently. Association rules statements that help uncover relationships between seemingly unrelated data. An example of an association rule is "If a customer buys eggs, he is 80% likely to also buy milk." The association rules has two parts, the antecedent (if) and the consequent (then). An antecedent is an item (or itemset) found in the data. A consequence is an item (or itemset) that is found in combination with an antecedent.

3.5 Evaluation

Evaluation is done by testing data with different minimum support and minimum confidence values to find the best values and rules. Here are the results of testing the data.

3.5.1 Analysis of the Effect of Minimum Support on Frequent Itemset

Table 3. Frequent Itemset

Item Set	Minimum Support				
	10%	20%	30%	40%	50%
1	19	9	4	4	4
2	50	20	6	6	6

3	46	16	4	4	2
4	14	5	1	1	0
TOTAL	129	50	15	15	12

The following item sets are formed from the minimum support from 10% to 50%. In Table 2, shows data for a minimum support of 10% produces 129 frequent itemsets with itemset of 4. Minimum support of 20% produces 50 frequent itemsets with itemset of 4. A minimum support of 30% produces 15 frequent itemsets with itemset of 4. Minimum support 40% produces 15 frequent itemsets with itemset of 4. Minimum support 50% produces 12 frequent itemsets with itemset of 3. In Table 3, it can be concluded that the greater the minimum support, the fewer the number of items produced [2][7] and the stronger the association relationship between attributes in the rules formed [20].

Table 4. Minimum Support 10%

Size	Support	Item 1	Item 2	Item 3	Item 4
1	0.994	PYO			
1	0.991	BON			
1	0.989	QBY			
...
4	0.032	PYO	BON	QBY	YSL
4	0.032	PYO	BON	QBY	SOR
4	0.032	PYO	BON	QBY	SUU

Based on Table 4, with a minimum support of 10%, it can see the itemsets formed and the items, for ex sample the itemset of four consists of classes or brands PYO, BON, Q BY and YSL.

Table 5. Minimum Support 20%

Size	Support	Item 1	Item 2	Item 3	Item 4
1	0.994	PYO			
1	0.991	BON			
1	0.989	QBY			
...
4	0.055	PYO	BON	QBY	TAF
4	0.048	PYO	BON	QBY	BBN
4	0.047	PYO	BON	QBY	HUP

Based on Table 5, with a minimum support of 20%, it can see the itemsets formed and the items. For ex sample the itemset of four consists of classes or brands PYO, BON, QBY and TAF.

Table 6. Minimum Support 30%

Size	Support	Item 1	Item 2	Item 3	Item 4
1	0.994	PYO			
1	0.991	BON			
1	0.989	QBY			
...
3	0.114	PYO	QBY	MCA	
3	0.114	BON	QBY	MCA	
4	0.113	PYO	BON	QBY	MCA

Based on Table 6, with a minimum support of 30%, it can see the itemsets formed and the items. For ex sample the itemset of four consists of classes or brands PYO, BON, QBY and MCA.

Table 7. Minimum Support 40%

Size	Support	Item 1	Item 2	Item 3	Item 4
1	0.994	PYO			
1	0.991	BON			
1	0.989	QBY			
...
3	0.114	PYO	QBY	MCA	

Table 10. Lift Ratio

No	Premises	Conclusion	Support	Confidence	Lift
1	MCA	PYO, BON	11.45%	97.63%	0.99185212
2	PYO	BON, QBY	97.32%	97.95%	1.00013798
3	MCA	QBY	11.52%	98.23%	0.99365002
4	BON	PYO, QBY	97.32%	98.25%	1.00008007

3	0.114	BON	QBY	MCA	
4	0.113	PYO	BON	QBY	MCA

Based on Table 7, with a minimum support of 40%, it can see the itemsets formed and the items. For ex sample the itemset of four consists of classes or brands PYO, BON, QBY and MCA.

Table 8. Minimum Support 50%

Size	Support	Item 1	Item 2	Item 3
1	0.994	PYO		
1	0.991	BON		
1	0.989	QBY		
...
2	0.115	QBY	MCA	
3	0.973	PYO	BON	QBY
3	0.114	PYO	BON	MCA

Based on Table 8, with a minimum support of 40%, it can see the itemsets formed and the items. For example the itemset of three consists of classes or brands PYO, BON and MCA.

3.5.2 Analysis of the Effects of Minimum Support and Minimum Confidence

At this stage, the rules are generated following the value of confidence that has been determined in this study. Confidence referred to in this study is the value of the tendency of an item with certain items to be purchased by the customer simultaneously. From a confidence value of 60% to 90%, it is expected to produce the best rule. The following is the rule result for each confidence value, which are:

Table 9. Number of Rule

MinConf	MinSup				
	10%	20%	30%	40%	50%
60%	292	109	31	31	18
70%	292	109	31	31	18
80%	292	109	31	31	18
90%	292	109	31	31	18

Based on Table 9, it can be seen that with minimum support 50% and minimum confidence of 90% produces 18 the number of rule. With the combination of minimum support and minimum confidence, the lift ratio can be seen in Table 10.

5	QBY	PYO, BON	97.32%	98.44%	1.00012702
6	MCA	PYO	11.57%	98.65%	0.99283225
7	BON, MCA	PYO	11.45%	98.68%	0.993117
8	BON	QBY	97.93%	98.86%	1.00003798
9	PYO	QBY	98.24%	98.87%	1.0000959
10	PYO, BON	QBY	97.32%	98.87%	1.00012702
11	MCA	BON	11.60%	98.94%	0.99877523
12	PYO, MCA	BON	11.45%	98.97%	0.99906169
13	QBY	BON	97.93%	99.06%	1.00003798
14	PYO	BON	98.43%	99.06%	1.00004895
15	PYO, QBY	BON	97.32%	99.07%	1.00008007
16	BON	PYO	98.43%	99.37%	1.00004895
17	QBY	PYO	98.24%	99.37%	1.0000959
18	BON, QBY	PYO	97.32%	99.37%	1.00013798

The lift ratio test stage produces a size for test the validity of the rules that have been formed. Lift ratio to know the strength of the association rules. Lift ratio is a comparison between confidence for a rule divided by benchmark confidence, which is assumed to be consequent and antecedent mutually independent. Consequent is a consequence or item that will be purchased after buying an antecedent. Antecedent is the reason that makes the item consequent. If the $K \rightarrow L$ rules are obtained, then K is antecedent and L is consequent. To get the lift ratio value using equation:

$$Lift\ Ratio = \frac{Confidence\ (K,L)}{Benchmark\ Confidence\ (K,L)} \quad [20]$$

To get the benchmark confidence value it self can be calculated using the following equation:

$$Benchmark\ Confidence = \frac{Nc}{N} \quad [20]$$

Information:

Nc = number of transactions with items that become consequent.

N = number of database transactions.

Lift ratio values greater than one indicate the benefits of these rules. The higher the lift ratio value, the greater the association strength. Lift ratio measures how important the rule is formed based on the value of support and confidence. Lift Ratio is a value that shows the validity of the transaction process and provides information on whether product K was purchased together with product L.

Based on Table10, it can be seen that the lift ratio for association rules has a greater value 1. This shows that all the rules are strong and valid to be used as a reference to find out the relationship or correlation between items [2][7]. The higher the lift ratio, the greater the strength of the association [21].

4. RESULT AND DISCUSSION

Based on the results of the study it can be seen that with a minimum support of 10% produces as many as four itemset with a total of 129 items and with a minimum support of 50% produces as many as three itemset with a total of 12 items.

Combination of minimum support is 10% and minimum support is 60%, minimum support is 10 % and minimum support of 70%, minimum support of 10% and minimum support of 80%, minimum support of 10% and minimum support of 90% resulting in the same number of association rules totaling 292. Then with a minimum support of 50% and minimum confidence of 90% resulting in association rules that at least 18 and the average lift ratio is more than 1.

Association Rules
[MCA] --> [PYO, BON] (confidence: 0.976)
[PYO] --> [BON, QBY] (confidence: 0.979)
[MCA] --> [QBY] (confidence: 0.982)
[BON] --> [PYO, QBY] (confidence: 0.982)
[QBY] --> [PYO, BON] (confidence: 0.984)
[MCA] --> [PYO] (confidence: 0.986)
[BON, MCA] --> [PYO] (confidence: 0.987)
[BON] --> [QBY] (confidence: 0.989)
[PYO] --> [QBY] (confidence: 0.989)
[PYO, BON] --> [QBY] (confidence: 0.989)
[MCA] --> [BON] (confidence: 0.989)
[PYO, MCA] --> [BON] (confidence: 0.990)
[QBY] --> [BON] (confidence: 0.991)
[PYO] --> [BON] (confidence: 0.991)
[PYO, QBY] --> [BON] (confidence: 0.991)
[BON] --> [PYO] (confidence: 0.994)
[QBY] --> [PYO] (confidence: 0.994)
[BON, QBY] --> [PYO] (confidence: 0.994)

Fig 7: Association Rules

In Figure 7, it can be seen that the rules result in minimum confidence are 97.63% and maximum confidence is 99.37%. The association rules can be seen that BON, QBY has a correlates with PYO, with a confidence value of more than 97%. Combination of minimum support and minimum confidence can be a recommendation for the right product promotion.

5. CONCLUSION

The results of the study concluded that:

1. The higher of the minimum support value used in the study will result in a smaller number of item sets. Accurate results for determining product promotion recommendations can be measured using a lift ratio. A transaction is said to be valid if it has a lift ratio value of more than 1, which means that in the transaction, K and L products are purchased simultaneously. The lift ratio

measures the importance of rules that have been formed based on the value of support and confidence. For experiments, the minimum support value is 10%-50% and the minimum confidence value is 60%-90%. Choosing the best combination of minimum support and minimum confidence to produce good association rules has a lift ratio value of more than 1.

2. Based on the analysis of the results of testing the data mining function using the FP-Growth algorithm produces the highest support value of 98.43%, the highest confidence value of 99.37% and the highest lift ratio of 1,00013798. The higher the value of the parameters used in processing with the FP-Growth algorithm, the fewer rules produced, the stronger the association relationship between the attributes in the rules formed.
3. The results of the study provide information on the products that are the most sold and the least sold. Product promotion recommendations can be done by selling best-selling products of top ten are MCA, PIC, TAF, BBN, HUP, KIE, QAR, RVX, NYX and SKT with less-salable products by bundling sales.
4. The results of the research provide information about what products are the most sold can be a product inventory system strategy. So that it can provide items to meet customer demand as well as proper item placement for best-selling of top ten are MCA, PIC, TAF, BBN, HUP, KIE, QAR, RVX, NYX and SKT with unsold items.

6. REFERENCES

- [1] A. Abdullah, "Rekomendasi Paket Produk Guna Meningkatkan Penjualan Dengan Metode FP-Growth," *Khazanah Inform. J. Ilmu Komput. dan Inform.*, vol. 4, no. 1, p. 21, 2018.
- [2] D. Sukma and D. Fitriah, "Data Mining Analysis with Association Rules Method to Determine the Result of Fish Catch using FP-Growth Algorithm," *Int. J. Comput. Appl.*, vol. 181, no. 15, pp. 7–15, 2018.
- [3] N. Arincy and I. S. Sitanggang, "Association rules mining on forest fires data using FP-Growth and ECLAT algorithm," *Proc. - 2015 3rd Int. Conf. Adapt. Intell. Agroindustry, ICAIA 2015*, pp. 274–277, 2016.
- [4] F. Fitriyani, "Implementasi Algoritma Fp-Growth Menggunakan Association Rule Pada Market Basket Analysis," *J. Inform.*, vol. 2, no. 1, 2016.
- [5] A. Wahana, D. S. Maylawati, M. Irfan, and H. Effendy, "Supply chain management using fp-growth algorithm for medicine distribution," *J. Phys. Conf. Ser.*, vol. 978, no. 1, 2018.
- [6] A. N. S. Putro and R. I. Gunawan, "Implementasi Algoritma FP-Growth Untuk Strategi Pemasaran Ritel Hidroponik (Studi Kasus : PT. HAB)," *J. Buana Inform.*, vol. 10, no. 1, p. 11, 2019.
- [7] M. I. Ghazali, R. Z. Ehwan, and W. H. Sugiharto, "Analisa Pola Belanja Menggunakan Algoritma Fp Growth, Self Organizing Map (Som) Dan K Medoids," *Simetris J. Tek. Mesin, Elektro dan Ilmu Komput.*, vol. 8, no. 1, pp. 317–326, 2017.
- [8] M. Kaur and S. Kang, "Market Basket Analysis: Identify the Changing Trends of Market Data Using Association Rule Mining," *Procedia Comput. Sci.*, vol. 85, no. Cms, pp. 78–85, 2016.
- [9] N. Hashimoto, S. Ozawa, T. Ban, J. Nakazato, and J. Shimamura, "A Darknet Traffic Analysis for IoT Malwares Using Association Rule Learning," *Procedia Comput. Sci.*, vol. 144, pp. 118–123, 2018.
- [10] W. Feng, Q. Zhu, J. Zhuang, and S. Yu, "An expert recommendation algorithm based on Pearson correlation coefficient and FP-growth," *Cluster Comput.*, pp. 1–12, 2018.
- [11] K. Sumangkut, A. S. M. Lumenta, and V. Tulenan, "Analisa Pola Belanja Swalayan Daily Mart Untuk Menentukan Tata Letak Barang Menggunakan Algoritma FP-Growth," *J. Tek. Inform.*, vol. 8, no. 1, 2016.
- [12] Midhunchakkaravarthy, Divya, D. Bhattacharyya, and T. H. Kim, "Evaluation of product usability using improved FP-Growth frequent itemset algorithm and DSLC – FOA algorithm for alleviating feature fatigue," *Int. J. Adv. Sci. Technol.*, vol. 117, pp. 163–180, 2018.
- [13] W. T. Lin and C. P. Chu, "A fast and parallel algorithm for frequent pattern mining from big data in many-task environments," *Int. J. High Perform. Comput. Netw.*, vol. 10, no. 3, pp. 157–167, 2017.
- [14] M. Yin, W. Wang, Y. Liu, and D. Jiang, "An improvement of FP-Growth association rule mining algorithm based on adjacency table," *MATEC Web Conf.*, vol. 189, pp. 0–6, 2018.
- [15] R. Anggrainingsih, N. R. Khoirudin, and H. Setiadi, "Discovering drugs combination pattern using fp-growth algorithm," *Int. Conf. Electr. Eng. Comput. Sci. Informatics*, vol. 4, no. September, pp. 735–738, 2017.
- [16] A. -, F. Marisa, and D. Purnomo, "Penerapan Algoritma Apriori Terhadap Data Penjualan di Toko Gudang BM," *Penerapan Algoritma Apriori Terhadap Data Penjualan di Toko Gudang BM*, vol. 1, no. 1, pp. 1–5, 2016.
- [17] Y. Gao, Q. Zhang, L. Chen, K. Wang, N. Chen, and H. Liu, "Research on application of FP-tree based association rule mining on test sequence in train control system," *Res. Appl. FP_tree based Assoc. rule Min. test Seq. train Control Syst.*, pp. 9993–9997, 2017.
- [18] H. Herasmus, "Analisa Customer Service System Menggunakan Metode Data Mining Dengan Algoritma Fp-Growth (Studi Kasus Di Pt Batamindo Investment Cakrawala)," *J. Tek. Ibnu Sina JT-IBSI*, vol. 2, no. 2, pp. 31–43, 2017.
- [19] K. Dharmarajan and M. A. Dorairangaswamy, "Analysis of FP-growth and Apriori algorithms on pattern discovery from weblog data," *2016 IEEE Int. Conf. Adv. Comput. Appl. ICACA 2016*, pp. 170–174, 2016.
- [20] A. R. Riszky and M. Sadikin, "Data Mining Menggunakan Algoritma Apriori untuk Rekomendasi Produk bagi Pelanggan," *J. Teknol. dan Sist. Komput.*, vol. 7, no. 3, p. 103, 2019.
- [21] Y. Jumiati and N. Bahtiar, "Pengembangan Sistem Informasi Data KB dan Analisis Pola Pemilihan Metode Kontrasepsi Menggunakan Algoritma Sql-Based Fp-Growth," *PERFORMA Media Ilm. Tek. Ind.*, vol. 15, no. 1, pp. 70–76, 2016.