Market Basket Analysis Using FP-Growth Algorithm to Design Marketing Strategy by Determining Consumer Purchasing Patterns

Jeffri Prayitno Bangkit Saputra [1], Silvia Anggun Rahayu [2,*], Taqwa Hariguna [3]

[1,3] Department of Information System, Amikom University Purwokerto, Indonesia
[2] Student of Computer Science Program, Amikom University Purwokerto, Indonesia
[1] prayitnojeffry@amikompurwokerto.ac.id, [2] silviaangunr@gmail.com, [3] taqwa@amikompurwokerto.ac.id
* corresponding author

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Abstract

The development and competition that exists in the business world today leads every manager or company to be more dexterous in making marketing strategies to increase sales. Various things are done to keep up with existing market competition, such as analyzing customer purchase transaction data to serve as a policy determination and decision-making system in making marketing strategies. In determining marketing strategies, it can be done by taking transaction data to see existing purchase or transaction patterns. Market Basket Analysis is part of a data mining method that uses the FP-Growth algorithm technique to find out associated products. This research uses data taken from sales transaction data archives as much as 150 sales transaction data and 26 product data. In this study, it is determined that the minimum support value is 50% and the minimum confidence is ≥ 0.75 From the test results, 9 products have superior support values and meet the minimum value. From the test results, a rule with a confidence value of 0.870 was obtained: D → W (if consumers buy Wardah Lightening Gentle Wash, then buy Azarine Sunscreen SPF50), and 0.808: A → E → O (if consumers buy Emina Face Wash, then buy Azarine Night Moisturizer and Himalaya Neem Mask).

Keywords: Data Mining, Association Rule, Market Basket Analysis, FP-Growth Algorithm

1. Introduction

The development and competition that exists in the business world today leads every manager or company to be more dexterous in making strategies that can attract consumer attention and ensure business continuity to increase sales. In the process of trading activities, especially transactions, it results in a lot of data stored in a company archive. However, the stored data is only used as an archive and is not utilized and will only increase. Transaction data that is only stored in an archive can actually be used by companies as an important source of information for decision-making materials in making a marketing strategy by knowing consumer purchasing patterns. Knowledge of the pattern of purchasing goods by consumers can be utilized in making a marketing strategy by making a purchase suggestion in the form of a certain product package based on products that have similar purchasing criteria in each transaction.

There are several studies that have been conducted related to association analysis on sales data. Research conducted by [1], [2]. By applying the FP-Growth algorithm, prescription transaction data can be utilized to produce important information in determining the layout pattern of goods according to consumer purchasing patterns. The results of the association rule can be used as input for the pharmacy in determining the layout pattern of goods at the pharmacy.

Research conducted by [3]. Applying the market basket analysis method to make policies and business strategies for PT Mora Telematics Indonesia using Association rule techniques. In this study, Market basket analysis uses the Frequent Pattern Growth (FP-Growth) algorithm to find patterns by applying a Tree data structure or called an FP-Tree. One of the patterns generated from the analysis of sales transaction data from January 2018 to April 2018 resulted in 7 association rules with the highest lift ratio value, namely if there is an OxygenHome 25 - Super Double installation, there will be an OxygenHome 15 - Super Double installation with a lift ratio of 4.59%, a support value of 3.125%, and a confidence value of 0.67%.

The first research conducted by [4] used the market basket analysis method with association rules to analyze transaction data in an online store. The results showed that products that are often purchased together are food products, beauty products, and household goods products. The conclusion of the above research is that the market basket analysis method with association rules can be used to analyze transaction data in various stores and find out products that are often purchased together in one shopping cart. This is beneficial for store owners to increase sales and offer products that suit customer needs. Based on several studies that have been conducted previously, it is proven that using the Market Basket Analysis method with the FP-Growth algorithm can be a solution for managing transaction data that is used to determine consumer purchasing patterns.

So as to minimize data into something meaningless and utilize the data collected to be used as a useful data set, an association analysis process will be carried out using association rule techniques using the FP-Growth algorithm which is used to determine consumer purchasing patterns. Consumer purchasing patterns can later be used as a marketing strategy by making a purchase recommendation in the form of a certain product package based on product criteria that have similar criteria from each transaction. With the aim of determining purchasing patterns that occur simultaneously in one transaction to be used as advice or recommendations in the form of certain product packages as a marketing strategy.

2. Literature Review

Research conducted by [5], [6] aims to improve the decision-making process for supermarkets in organizing their product catalogs. The research focuses on determining the relationship between products purchased at a particular store by utilizing the Apriori algorithm and Market Basket Analysis. The results of this study can help companies to strategize better in placing products close to each other to increase the likelihood of consumers buying them together.

Research conducted by [7]. By utilizing transaction data to provide information for making menu packages at Angkringan Waru and also providing information about the relationship between food and beverage menu items based on transaction data using the FP-Growth algorithm. The results of this study are able to provide recommendations for Angkringan Waru menu packages which include two items, namely snacks and drinks to make it easier for customers to choose menu packages and help sellers increase their overall sales. This is intended to provide information for making menu packages at Angkringan Waru and also provide information about the relationship between food and beverage menu items based on transaction data.

Research conducted by [8] on Market Basket Analysis, customer purchasing patterns are identified by identifying important associations between products purchased together. The results showed that if the most popular items are used, it is possible to get almost the same frequent itemset and association rules in a short time compared to the output obtained by counting all items.

3. Methodology

3.1. Computation Flow

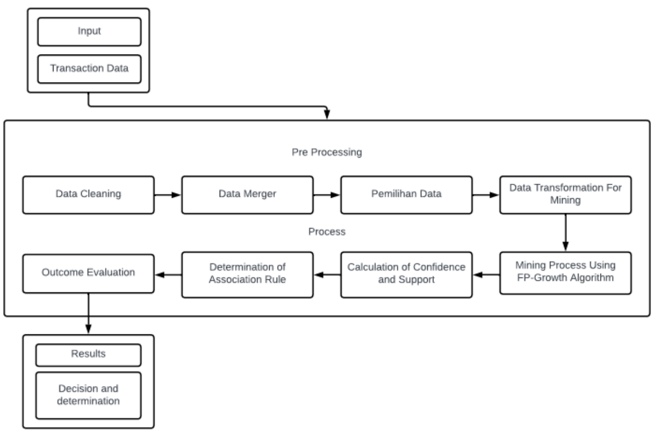

Figure. 1. Computation flow

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Figure 1 is an overview of the block diagram on the implementation using association rules and the FP-Growth algorithm that plays a role in the data processing process. In the block diagram above, it is explained as follows:

1) The data processing process starts from inputting transaction data and then there will be a pre-processing stage for the data.
2) Data cleaning with the aim of removing and modifying irrelevant data and data duplication.
3) Combining data that has been done by the data cleaning process according to the similarity of the criteria of each data.
4) Selection of data that is in accordance with the analysis needs for data processing that will be executed at a later stage.
5) Data transformation for mining is a step taken by changing the data in a form that is suitable for the data mining process or called normalization with the aim of changing the data measurement scale in another form according to research needs to meet the assumptions of the analysis and data processing process.
6) The mining process using the FP-Growth algorithm aims to find products that are often purchased together in one shopping cart by customers by going through several stages, such as frequency table or calculating the frequency of occurrence of each item in the dataset, creating an FP-Tree, which is about itemset patterns that often appear in the dataset or in the form of nodes that show the relationship between items, Frequent pattern mining, the FP-Growth algorithm will search for frequent patterns by following the data flow between nodes in the FP-Tree. The detected patterns will be stored in the frequent pattern table and the result will store information about the detected frequent patterns, as well as their frequency of occurrence in the dataset.
7) Calculation of confidence and support to evaluate the strength of a pattern detected in the dataset, where the support value is a measure of the occurrence of a pattern in the dataset, while confidence is a measure of confidence that a pattern will appear after another pattern appears.
8) Determination of association rule which is a stage to determine a pattern detected in the dataset that shows the relationship between items by determining the minimum value to be used as a reference in finding patterns that meet the predetermined support and confidence criteria.
9) Final evaluation is the process of evaluating the strength and validity of the patterns detected in the dataset.
10) The results of the decision and determination which is the final stage of the transaction data processing process at Toko Gudang Kosmetik Purwokerto with the FP-Growth Algorithm in the form of a list of association patterns (association rules) detected in the dataset where each pattern is stored in an association rule table, which stores information about the pattern, as well as its support and confidence values.

3.2. Dataset

This paper mainly studies the solar MPPT algorithm, mainly using the WNN algorithm. In this paper, several common MPPT control methods are analyzed, and the WNN algorithm selected in this paper is understood from the midpoint. Then, this paper describes the structure design of the WNN maximum power tracking control algorithm, and describes the structure and working principle of photovoltaic cells. This paper describes the WNN MPPT algorithm structure to track and calculate the MPP of solar energy. This paper analyzes and compares the power output power of MPPT mode through the simulation experiment of the solar photovoltaic system, and studies the output voltage of the solar charging panel in the charging process, and realizes the tracking of solar MPP through the experimental verification.

3.3. Market Basket Analysis

In a business company, market basket analysis presents information related to several products that have the possibility of being purchased simultaneously and determines the most appropriate product to promote. The application of the association rule method in market basket analysis has two stages to find and generate information and knowledge from a database. The steps to be taken are as follows:

1) Searching for frequent itemsets

   At this stage, there is a search for a combination of items that meet the support requirements in the transaction database. In finding the combination of items, it can be done by using the support calculation formula as follows:

$$Support\ (A\ => \ B\ =\ P\ (A \cup B) \tag{1}$$

2) Forming association rules

After all frequent itemsets are known, the next step is to form an association rule that can fulfill a confidence value. To find out the confidence value, it can be done by using the calculation formula as follows:

$$Confidence\colon P(A \cap B) \ = \sum Transactions\ Containing\ A\ and\ B \times 100\% \qquad (2)$$

According to equation 3, it can be concluded that the support value of itemset or product variation group A against itemset B is equal to the probability of itemsets A and B combined. Meanwhile, equation 4 explains that the confidence percentage of itemset A against itemset B is equal to the probability of the combination of itemsets A and B divided by the probability of itemset A.

3.4. FP-Growth Algorithm

Frequent Pattern Growth (FP-Growth) is an alternative method to determine the most frequent itemset in a data set. Determination of frequent itemsets using the FP-Growth algorithm will be done by creating a data structure in the form of a tree or called FP-Tree. In the FP-Growth method, there are 3 stages, as follows:

1) Establishing a conditional pattern base. A sub-database known as the conditional pattern base stores information about the prefix path and suffix patterns. The FP-Tree that has been built in the previous step is used to derive the conditional pattern base generation. [9], [10].
2) Conditional FP-Tree Generation. At this stage, there is a process that involves adding the support count of each item with each conditional pattern base. After this step, a conditional FP-Tree will be generated for each item that has a support count greater than or equal to the minimum support. [11], [12].
3) Search for frequent itemsets. At this stage, to get frequent itemsets, we must first combine the itemsets found in each conditional FP-Tree. If the conditional FP-Tree contains only a single path, then this step is not required [13]–[16]. On the other hand, if the conditional FP-Tree has more than one branch, then the FP-growth generation will be done recursively (by calling this process again).

3.5. Association Rule

Association Rules are a very helpful tool in the business world as they can be used to determine which goods and services are most likely to be purchased in conjunction with each other. To perform an association rule search, it is necessary to have a variable measure of confidence, which the user is tasked with defining such measures are the support and confidence values [17]–[22].

In determining the minimum support value of an item, it can be obtained by using equations (3) and (4) as listed below:

$$Support\ (A) \ = \frac{(Number\ of\ Transactions\ Containing\ A)}{(Total\ Transaction)} \qquad (3)$$

$$Support\ A \cap B \ = \frac{(Number\ of\ Transactions\ Containing\ A\ and\ B)}{(Total\ Transaction)} \qquad (4)$$

Meanwhile, in determining the minimum confidence can be determined by the formula equation (5) as below:

$$Confidence\ (A \rightarrow B\ ) \ = \ P\ (A|B) \ = \frac{(Number\ of\ Transaction\ Containing\ A\ and\ B)}{(Total\ Transaction)} \qquad (5)$$

The association rule mining procedure is a way to find relationships between items in a dataset.

4. Results and discussion

4.1. Data Processing

Here in Table 1 there is transaction data used as research material in the form of raw data or no cleaning process has been carried out.

Table. 1. Transaction data

No	InvoiceNo	Description	Quantity	InvoiceDate	CustomerID
1	01092022-101027	EM10005 - EM Face Serum	3	01/09/2022	2011VP0022
2	01092022-101027	AZ10021 - AZ Brightening C Glow Serum	1	01/09/2022	2011VP0022
3	01092022-101027	NF10001 - GW Yellow VIT C 125ML	2	01/09/2022	2011VP0022
4	01092022-101028	EM10002 - EM Face Wash	2	01/09/2022	2011VP0228
5	01092022-101028	WD10003 - WD Moisturizer SPF 28	2	01/09/2022	2011VP0228
6	01092022-101028	GW10002 - GW Pink 125ml	1	01/09/2022	2011VP0228
...	......	......	....	....	....
4998	31092022-103021	EM10002 - EM Face Wash	1	31/09/2022	2011VP3127
4999	31092022-103021	WD10003 - WD Moisturizer SPF 28	1	31/09/2022	2011VP3127
5000	31092022-103021	AZ10018 - AZ Acne-Oil Free Brightening	1	31/09/2022	2011VP3127

Table. 2. Transaction data code version

TID	ITEM
1	{B,Q,X}
2	{A,E,F,J,M,O,P,Q,R,U,V,X}
3	{A,C,H,L,N,O,P,S,X}
…	…
150	{A,E,P,T,X}

The following in Table 2 is the transaction data used as research material and has been carried out a data adjustment process so that the data can be read during the mining process using the FP-Growth algorithm.

Table. 3. Normalization results

Binominal												
NoTrs	A	B	C	D	E	F	G	H	I	J	L - Y	Z
1	0	1	0	0	0	0	0	0	0	0	..	0
2	1	0	0	1	1	0	0	0	1	0	...	0
3	1	0	1	0	0	0	1	0	0	0	...	0
4	1	0	0	0	0	1	0	0	0	0	...	0
5	0	1	0	1	1	1	0	1	0	0	...	0
6	0	0	0	0	1	1	0	0	0	0	....	0
7	0	0	0	1	1	0	0	0	1	0	....	0
8	0	0	1	0	0	0	1	0	0	1	...	0
9	1	0	0	1	0	1	0	0	0	0	...	0
10	0	0	0	1	1	0	0	1	0	0	...	0
11-144	....	....	.....	.....	....	.....	....	....	....	....	....	.....
145	1	1	0	1	1	1	0	0	0	0	....	0
146	0	0	0	1	0	1	0	0	0	0	....	0
147	1	0	0	1	1	1	0	0	0	0	....	0
148	1	0	0	1	0	1	0	0	0	0	....	0
149	0	0	1	0	1	1	0	0	0	0	....	0
150	1	0	0	0	1	0	0	0	0	0	....	0
Total	72	22	25	75	71	69	9	8	11	11	10	8

Table 3 is the result of normalization of transaction data that has been cleaned, namely a total of 150 data.

Table. 4. Data initialization

ITEM	Code
EM Face Wash	A
EM Face Serum	B
EM Moisturizing Cream	C
...	...
GW Yellow VIT C 125ML	Z

In table 4, there is a process of data initialization or giving code marks to each itemset. This step is done to facilitate the process of calculating and processing data in the next process. For example, EM Face Wash items or products are given initialization or code A, EM Face Serum is given code B, EM Moisturaizer Cream is given code C, and GW Yellow VIT C 125 ml products are given code Z.

Table. 5. Initialized transaction data

TID	ITEM
1	{B,Q,X}
2	{A,E,F,J,M,O,P,Q,R,U,V,X}
3	{A,C,H,L,N,O,P,S,X}
...	...
150	{A,E,P,T,X}

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In table 5 is transaction data that has been initialized based on each product itemset. For example in TID or transaction 1 sold products B,Q,X and transaction 2 sold products A,E,F,J,M,O,P,Q,R,U,V,X Transaction data that has been initialized will be used as sample data to be converted into binominal format which can be seen in the table below:

Table. 6. Initialized transaction data

A	B	C	D	E	...	Y	Z
0	1	0	0	0	...	0	1
1	0	0	0	1	...	0	0
1	0	1	0	0	...	0	0
...	...	...	...	...	...	...	...
1	0	0	0	1	...	0	0

In table 6 there is a binominal table or fromat with numbers 1 and 0, number 1 indicates that the product was sold at that transaction number and number 0 indicates that the product was not sold at that transaction number. After the data is tabular, the data is ready to be imported into the RapidMiner tools. To be processed in the RapidMiner tool, the data must be converted into binomial data.

Table. 7. Frequency of each buyer making transactions

TID	Total Transaction
1	3
2	12
3	9
...	...
150	5

Table 7 is the result obtained from the data processing process with binominal format, namely in the form of the total number of product sales in each transaction that has been carried out. TID in the table above is interpreted as a transaction number or transaction id. While the total transaction is the total result of each product purchased in each transaction.

Table. 8. Frequency of occurrence of each item/product

Code	Product / Item	Frequency
A	EM Face Wash	72
B	EM Face Serum	22
C	EM Moisturizing Cream	25
...	...	...
Z	GW Yellow VIT C 125ML	8

Table 8 shows the frequency of each item/product obtained from the data processing process with binomial format, which is in the form of total sales of each product from all sales transactions. It can be concluded with an example based on the table above that the product with code A or EM Face Wash in a total of 150 product transactions was able to sell 72 items.

The results of the Frequency of Occurrence of Each Item / Product are used for calculations with Association Rule techniques which can be determined by two parameters, namely support (support value) and confidence (certainty value). Support is a measure that shows the level of dominance of itemsets from all transactions. The following is the formula for the support value in the FP-Growth algorithm:

$$Support = (X \cup Y) count / n \quad (6)$$

Table. 9. Frequency and support value

Products	Frequency	Support Value
EM Face Wash	72	56%
EM Face Serum	22	40%
EM Moisturizing Cream	25	36%
...	...	...
GW Yellow VIT C 125ML	8	20%

Table 9 is the calculation process to determine the support value for each product based on the frequency or total sales of each product. For example, the EM Face Wash product with a frequency or total sales of 72 items produces a support value of 56%.

In this study, it is determined that the minimum support count value is 50% so that later products that have a support value below 50% will not be detected to enter the FP-Tree formation stage.

After calculating the frequency of occurrence of each item, it can be seen that the products that are above the value of support count = 50% are items or products with frequencies above 9 in the form of products with initialization A, D, E, F, O, P, Q, R, and X. These 9 products will be influential and will be included in the FP-Tree, the rest are not used because they do not have a significant effect. These 9 products will be influential and will be included in the FP-Tree, the rest of the other items are not used because they have no significant effect.

Table. 10. Products that meet the minimum support

Code	**Product Name**
A	EM Face Wash
D	WD Lightening Gantle Wash
E	WD Moisturizer SPF 28
F	WD Sunscreen
O	HY Himalaya Neem Mask
P	AZ Moisturaizer SPF 25
Q	AZ Night Moisturaizer
R	AZ C White Wachial Wash

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X	AZ Night Moisturaizer

Table 10 is the result or list of products that meet the minimum support count value above 50%, for example, products with code A, namely EM Face Wash, are included in the criteria that meet the minimum support count value, namely with 56% support. The next step in the fp-growth algorithm process is tree formation. This is done based on table 4.9 The formation of the fp-tree starts from TID 1 to TID 150. The following is a sample of TID 1 formation, namely with itemset {Q,X}.

In TID 1 consists of products {Q,X}, which can be interpreted as transaction number 1 there are two products that are sold and meet the minimum support value, namely product Q or Azarine Night Moisturaizer and product X or GW Pink 125ml. TID readings are taken from 1 to 150, in this study TID 150 readings will not be displayed because it will be difficult to see in the form of an image. After all TID readings are done, the next step is to look for trajectories that end with the number of supports (A), (D), (E), (F), (O), (P), (Q), (R), and (X) or products with support values above 50%. The reading of the node trajectory is done up to 9 products. An example of the process of forming each node or node trajectory A can be seen in Figure 2. Figure 3 is the formation of an FP-Tree with paths containing node A, namely {D,X,A}, { X,F,A} and {R,A}. Node A is defined as a product that has a relationship with product A. For example, if a consumer buys product A, he will buy product D and product X, as well as consumers who buy product X and product F will also buy product A, and similarly, consumers who buy product R will simultaneously buy product A in one transaction.

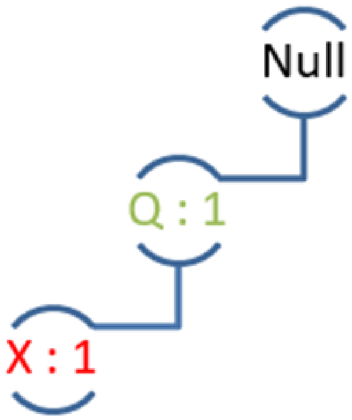

Figure. 2. TID 1

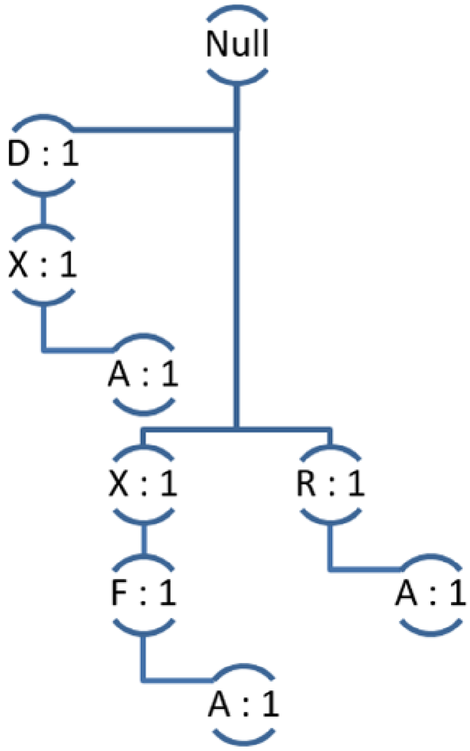

Figure. 3. Trajectory of vertex A

In the Conditional FP-Tree table above is the result of the conclusion of the conditional pattern base table or the number of products that have a relationship with 9 products that meet the minimum support value. For example, in item D, the conditional FP-Tree for product Q is 6, product T is 5, product F is 6, product S is 1, product X is 3, product A is 7, product P is 3, product E is 5, product O is 4, product R is 2, and product W is 1. In table 11, the calculation process to form a conditional FP-tree is done by looking for itemsets that often appear with the same suffix. After creating the conditional pattern and conditional FP-tree, the next step is to determine the minimum support and minimum confidence values. In this stage, the formulas previously explained in the basic theory are used to determine the support and confidence values for each itemset. The results are as follows.

Table. 11. Rule formed

Rule	Support	Confidence
D,W	13%	87%
X,E,O	14%	80,8%

In this study, it is determined that the minimum confidence value is ≥ 0.75. So that from the calculation of confidence in the pattern formed above, the Association Rule that meets the confidence requirement ≥ 0.75 is: D → W = 0.870 (if consumers buy Wardah Lightening Gantle Wash, then buy Azarine Sunscreen SPF50), X → E → O = 0.808 (if consumers buy Emina Face Wash, then buy Azarine Night Moisturaizer and Himalaya Neem Mask).

5. Conclusion

Overall, from 150 sales transaction data and 26 product data, 9 products are produced that have superior support values and meet the minimum support value. Consumers tend to buy items that are interconnected as in : D → W = 0.870 (if consumers buy Wardah Lightening Gantle Wash, then buy Azarine Sunscreen SPF50), X → E → O = 0.808 (if consumers buy Emina Face Wash, then buy Azarine Night Moisturaizer and Himalaya Neem Mask). By utilizing the rules obtained, new information related to the research results regarding customer purchasing patterns in each transaction made. So that it can be used to help companies, especially shop to increase sales.

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