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APPLICATION OF DATA MINING IN GROCERY SALES USING THE FP-GROWTH ALGORITHM

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Abstract: Sales of basic needs today require the use of information technology. The problem that often occurs is providing the best service to customers with the right business strategy to avoid business losses. Business actors are required to determine strategies that can increase sales of the products being sold. It is often found that transaction data is always increasing but is often not utilized properly. Another way is to determine a basic food sales strategy using data mining techniques. The technique used is the Fp-Growth Algorithm, which is an algorithm that generates frequent itemsets which will later be useful in the process of determining rules that can generate a choice. The Fp-Growth Algorithm is a development of the Apriori Algorithm. It's just that the Fp-Growth Algorithm uses tree development in searching for the types of goods that are often purchased. The data used are 26 types of basic food products and 30 transaction data. In this study, the minimum support value was 30% and the minimum confidence value was 60%.

INTRODUCTION

Technological developments are developing very quickly and have a big impact in various fields. There is no exception that competition in the business world in the current era is very tight, especially in the field of selling staple food products and daily necessities in society. The transaction data held continues to increase every day, but it is often found that the transaction data held is only stored and not utilized properly. The problem that is also often faced in this case is providing the best service to buyers which can later be used to set business strategies that are right on target to avoid losses.

Many factors cause this. One of the contributing factors is the difficulty of generating opportunities related to data patterns on sales of basic food products, which has a negative impact on product sales results which sometimes go up and down. This is because the products that are most sold and are interconnected are still not well organized, so that consumer purchasing patterns for a selected product are not analyzed properly to determine the stocking strategy for the product to be sold. Therefore, good business techniques are needed to get maximum profits in the right way.

One technique that can be used to determine consumer purchasing pattern strategies is data mining techniques. Frequent Pattern Growth is an alternative algorithm that can be used to determine the data set that appears most frequently in a data set

THEORETICAL BASIS

A. Data Mining

Data Mining is a series of processes for mining very large amounts of data so as to obtain information from that data collection. Information generated by extracting and searching for very important patterns from a data set or database. Data Mining is used to search for information in a database in very large quantities so it is also called a Knowledge Discovery Database.

B. Association Rules

Association Rule is a Data Mining technique for finding associative rules between a combination of items. The association rule algorithm will use training data, in accordance with the meaning of data mining, to generate knowledge. What knowledge will be generated in the association rules. Knowledge to find out shopping items that are often purchased simultaneously at one time. Association rules in the form of "if...then..." or "if...then..." are knowledge resulting from the function of association rules.

Association rules have two stages of work, namely as follows.

1. Search for frequent itemsets.
2. Define conditions and results (for conditional association rules).

Association rules are obtained from the results of calculations consisting of 2 measures, namely:

1. Support

Support aims to find out how high the level of dominance of itemsets is in transaction data. Support will determine whether searching for confidence values in an itemset is feasible or not. Support can also be used to determine the level of dominance of a single item.

In determining the support value of an item, it can be obtained using the formula as below:

$$Support = \frac{Number\ Of\ Transaction\ \ A}{Total\ Transaction}\ x\ 100$$

$$Support\ A\ \cap B = \frac{Number\ Of\ Transaction\ \ A\ dan\ B}{Total\ Transaction}\ x\ 100$$

1. *Confidence*

Confidence is a relationship that conditionally shows the relationship between two items (for example, if a customer buys item A, calculate the probability of how often the customer also buys item B).

$$\boldsymbol{Confidence}\ =\ \mathbf{P}\ (\ \mathbf{A}\ |\ \mathbf{B}\ ) = \frac{Number\ Of\ Transaction\ A\ dan\ B}{Number\ Of\ Transaction\ A}\ x\ 100$$

C. Algoritma *FP-Growth*

The FP-Growth algorithm is a development of the Apriori algorithm. FP-Growth is a method that builds a very dense data structure (FP-Tree) to compress the original transaction database. The FP-Growth algorithm is an efficient method where mining is carried out with a prefix-tree structure on a complete item set. The tree structure stores information about frequent patterns.

D. RapidMiner

RapidMiner is a data science software platform developed by the company of the same name, which provides a unified environment for machine learning, deep learning, text mining, and predictive analytics. . It is used for business and commercial applications as well as for research, education, training, rapid prototyping, and application development and supports all steps of the machine learning process including data preparation, results visualization, validation and optimization. RapidMiner was developed with an open core model.

RESULTS AND DISCUSSION

A. Discussion

In this research discussion, there are several discussion results that must be resolved. The stages that will be carried out in this research are data analysis, data representation, and data analysis results.

1. Data analysis

The initial stage was carried out to analyze data specifically for the sale of basic food products at the Khalilla basic food wholesaler with the aim of finding patterns in the sale of basic food products that are interconnected with each other in a transaction. The stage that will be carried out in this research is to prepare the data. The data processed is research data from the basic food wholesaler Khalilla from December 2022 to January 2023 with a total of 241 data records obtained. In order to obtain data analysis, the sales data is exported into an Excel database sheet because Microsoft Excel is a spreadsheet so that it can later be used to support data analysis. Microsoft Excel is very useful for supporting several data mining applications, where data mining software applications are used for testing and also implementing data mining. Data mining itself is the process of mining data to obtain new knowledge or important information from databases, especially databases on sales of basic food products.

2. Data *Representation*

The characteristic of the FP-Growth algorithm is that the data structure used is in the form of a tree, which is also known as FP-Tree. By using FP-Tree, the FP-growth algorithm can extract frequent Itemsets from FP-Tree. Itemset and frequent mining using the FP-Growth algorithm will be carried out by generating a tree data structure or what is called FP-Tree. FP-Growth can be divided into 3 stages, namely as follows:

1. Conditional pattern base generation stage.
2. Conditional FP-Tree generation stage.
3. Frequent itemset search stage.

These three stages are the steps that will be taken to determine frequent itemsets. The following are the manual calculation stages of the Fp-Growth Algorithm. In the process of implementing the Fp-Growth Algorithm, there are several stages that must be carried out. The table below is a manual calculation to find frequent itemsets containing 30 sample transaction data from grocery wholesaler Khalilla.

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Table I

Transaction Data

No	Transaction_ID	Item Name
1	TRX - N23110	ABC Sardines in Chili Sauce 425 g (A)
		Rice 1 KG (C)
		Bimoli Pouch Cooking Oil (E)
		Light Snacks (G)
		Sugar 1 KG (J)
		Instant noodles (M)
		Bulk Cooking Oil (O)
		Coconut cream Sun Kara (S)
		Chili sauce Indofood (T)
		Chicken eggs (W)
		Flour (Y)
		Vinegar Dua Angsa (Z)
2	TRX - Y34OP1	Rice 1 KG (C)
		Sack Rice 5 KG (D)
		Sugar 1 KG (J)
		Gulaku packeged 1 KG (K)
		Soy sauce Bango 210 ML (L)
		Instant noodles (M)
		Nutrijell Jelly (P)
		Chili sauce Indofood (T)
		Chicken eggs (W)
		Flour (Y)
3	TRX - E12679	ABC Sardines in Chili Sauce 425 g (A)
		Sack Rice 5 KG (D)
		Light Snacks (G)

P.Issn : 2808-859X
E.Issn : 2809-0853

No	Transaction_ID	Item Name
		Sugar 1 KG (J)
		Gulaku Packeged 1 KG (K)
		Soy sauce Bango 210 ML (L)
		Instant noodles (M)
		Bulk Cooking Oil (O)
		Coconut cream Sun Kara (S)
		Chili sauceIndofood (T)
		Sweetened Condensed Chocolate Milk(U)
		Chicken eggs(W)
		Flour(Y)
4	TRX - NK5611	Ajinamoto (Flavoring) (B)
		Rice 1 KG (C)
		Downy Perfuming clothes(H)
		Sugar1 KG (J)
		Gulaku Packaging 1 KG (K)
		Soy sauce Bango 210 ML (L)
		Mie Instan (M)
		Bulk Cooking Oil (O)
		Nutrijell Jelly (P)
		Coconut cream Sun Kara (S)
		Chili sauceIndofood (T)
		Chicken eggs(W)
		White Rice Flour(X)
5	TRX - T34U11	Ajinamoto (Flavoring) (B)
		Rice 1 KG (C)
		Bimoli Cooking oilPouch (E)
		Downy Perfuming clothes(H)
		Gulaku Packaging 1 KG (K)
		Bulk Cooking Oil (O)

P.Issn : 2808-859X
E.Issn : 2809-0853

No	Transaction_ID	Item Name
		Chili sauceIndofood (T)
		Sweetened Condensed Chocolate Milk(U)
		Chicken eggs(W)
		White Rice Flour(X)
		Flour(Y)
6	TRX - 1N21UN	ABC Sardines in Chili Sauce 425 g (A)
		Rice Sacks 5 KG (D)
		Bimoli Cooking oilPouch (E)
		Table Salt Dolpin 250 g (I)
		Gulaku Packaging 1 KG (K)
		Bulk Cooking Oil (O)
		Rinso Powdered Detergent (Q)
		Coconut cream Sun Kara (S)
		Chili sauceIndofood (T)
		Sweetened Condensed Chocolate Milk(U)
		Chicken eggs(W)
7	TRX - K21N11	Ajinamoto (Flavoring) (B)
		Table Salt Dolpin 250 g (I)
		Rinso Powdered Detergent (Q)
		Royco Broth Powder (R)
		Chicken eggs(W)
		White Rice Flour(X)
		Flour(Y)
8	TRX - 54W11E	Rice 1 KG (C)
		Bimoli Cooking oilPouch (E)

P.Issn : 2808-859X
E.Issn : 2809-0853

No	Transaction_ID	Item Name
		Light Snacks (G)
		Soy sauce Bango 210 ML (L)
		Bulk Cooking Oil (O)
		Coconut cream Sun Kara (S)
		Chili sauceIndofood (T)
		Chicken eggs(W)
		White Rice Flour(X)
9	TRX - UI1234	Rice Sacks 5 KG (D)
		Bimoli Cooking oilPouch (E)
		Blue Band Multipurpose (F)
		Sugar1 KG (J)
		Drink Packaging (N)
		Bulk Cooking Oil (O)
		Teeh Packaging (V)
		Chicken eggs(W)
		Flour(Y)
10	TRX - R412JK	Ajinamoto (Flavoring) (B)
		Rice 1 KG (C)
		Table Salt Dolpin 250 g (I)
		Sugar1 KG (J)
		Gulaku Packaging 1 KG (K)
		Soy sauce Bango 210 ML (L)
		Mie Instan (M)
		Drink Packaging (N)
		Chili sauceIndofood (T)
		Sweetened Condensed Chocolate Milk(U)
		Chicken eggs(W)
Transaction up to 30 :		
30	TRX - UY1234	Table Salt Dolpin 250 g (I)

No	Transaction_ID	Item Name
		Soy sauce Bango 210 ML (L)
		Drink Packaging (N)
		Bulk Cooking Oil (O)

Table II

Frequency of Appearance of Each Item/Product

Item	Name Item	Frequency
A	ABC Sardines in Chili Sauce 425 g	11
B	Ajinamoto (Flavoring)	7
C	Rice 1 KG	15
D	Rice Sacks 5 KG	9
E	Bimoli Cooking oil Pouch	10
F	Blue Band Multipurpose	2
G	Light Snacks	6
H	Downy Perfuming clothes	6
I	Table Salt Dolpin 250 g	8
J	Sugar1 KG	10
K	Gulaku Packaging 1 KG	8
L	Soy sauce Bango 210 ML	14
M	Mie Instan	14
N	Drink Packaging	11
O	Bulk Cooking Oil	19
P	Nutrijell Jelly	6
Q	Rinso Powdered Detergent	5
R	Royco Broth Powder	6
S	Coconut cream Sun Kara	8
T	Chili sauce Indofood	14
U	Sweetened Condensed Chocolate Milk	9
V	Teeh Packaging	3
W	Chicken eggs	22

Item	Name Item	Frequency
X	White Rice Flour	7
Y	Flour	9
Z	Vinegar Dua Angsa	2

After all the frequencies of the items appear, the product names are sorted based on the highest frequency to the smallest, and can be seen in the table below:

Table III

Table Frequency and Value of Support

Item Name	Frequency	Support Value
Chicken eggs(W)	22	73.33%
Bulk Cooking Oil (O)	19	63.33%
Rice 1 KG (C)	15	50%
Soy sauce Bango 210 ML (L)	14	46.67%
Mie Instan (M)	14	46.67%
Chili sauce Indofood (T)	14	46.67%
Drink Packaging (N)	11	36.67%
ABC Sardines in Chili Sauce 425 g (A)	11	36.67%
Bimoli Cooking oil Pouch (E)	10	33.33%
Sugar1 KG (J)	10	33.33%
Rice Sacks 5 KG (D)	9	30%
Sweetened Condensed Chocolate Milk(U)	9	30%
Flour(Y)	9	30%
Gulaku Packaging 1 KG (K)	8	26.67%
Coconut cream Sun Kara (S)	8	26.67%
Table Salt Dolpin 250 g (I)	8	26.67%
Ajinamoto (Flavoring) (B)	7	23.33%
White Rice Flour(X)	7	23.33%
Light Snacks (G)	6	20%
Downy Perfuming clothes(H)	6	20%

Item Name	Frequency	Support Value
Nutrijell Jelly (P)	6	20%
Royco Broth Powder (R)	6	20%
Rinso Powdered Detergent (Q)	5	16.67%
Teeh Packaging (V)	3	10%
Blue Band Multipurpose (F)	2	6.67%
Vinegar Dua Angsa (Z)	2	6.67%

After calculating the frequency of appearance of each item, it is known that items that are above the support count value = 40% or items with a frequency above 14 are:

1. Chicken Eggs (W): 22
2. Bulk Cooking Oil (O): 19
3. Rice 1 KG (C): 15
4. Bango Soy Sauce 210 ML (L): 14
5. Instant Noodles (M): 14
6. Indofood Chili Sauce (T): 14

The 6 items above will have an effect and will be included in the fp-tree, the rest (A, B, D, E, F, G, H, I, J, K, N, P, Q, R, S, U , V, X, Y, and Z) are not used because they have no significant effect.

Table IV

Transactions tailored to the frequent list

TID	Item
1	{ W, O, C, M, T }
2	{ W, C, L, M, T }
3	{ W, O, L, M, T }
4	{ W, O, C, L, M, T }
5	{ W, O, C, T }
6	{ W, O, T }
7	{ W }
8	{ W, O, C, L, T }
9	{ W, O }

TID	Item
10	{ W, C, L, M, T }
11	{ W, O, L, T }
12	{ W, C, T }
13	{ O, L, M }
14	{ W, O, C, L, M, T }
15	{ W,O, L, T }
16	{ C, O }
17	{ W, C, L, M }
18	{ C }
19	{W, L }
20	{ W, C }
21	{ O, M }
22	{ C, T }
23	{ W, O, C, L, M }
24	{ W, O, M }
25	{ W, O, L, M }
26	{ W, O, M, T }
27	{ W }
28	{ O, M }
29	{ C }
30	{ O, L }

After checking the frequent itemset for several suffixes, the results are summarized in the table below.

Table V

Frequent Itemset Results

Suffix	***Frequent Itemset***
T	{ {C, T}, {W, O, T}, {W, O, C, T}, {W,O, C, M, T}, {W, O, C, L, T}, {W, O, C, L, M, T}, {W, O, M, T}, (W, O, L, M, T}, {W, O, L, T}, {W, C, T}, {W, C, L, M, T}}

Suffix	***Frequent Itemset***
M	{{W, O, C, M}, {W, O, C, L, M}, {W, O, M}, {W, O, L, M}, {W, C, L, M}, {O, L, M}, {O, M}
L	{{W, O, C, L}, {W, L}, {W, O, L}, {W, C, L}, {O, L}}
C	{{C}, {W, O, C}, {W, C}}
O	{{W, O}, {O}}
W	{{W}}

After knowing the results of the frequent itemsets in Table 4.9, the confidence value can be calculated which can be seen in the table below:

Table VI

Conditional Pattern Base

Suffix	**Conditional Pattern Base**
T	{{C : 1}, {W, O : 1}, {W, O, C : 1}, {W,O, C, M : 1}, {W, O, C, L : 1}, {W, O, C, L, M : 2}, {W, O, M : 1}, (W, O, L, M : 1}, {W, O, L : 2}, {W, C : 1}, {W, C, L, M : 2}}
M	{{W, O, C : 1}, {W, O, C, L : 3}, {W, O : 4}, {W, O, L : 2}, {W, C, L : 3}, {O, L : 1}, {O : 2}}
L	{{W, O, C : 4}, {W : 1}, {W, O : 4}, {W, C : 3}, {O : 2}}
C	{{W, O : 6}, {W : 5}}
O	{{W : 14}}

Table VII

Conditional Fp-Tree

Item	**Conditional Fp-Tree**
T	<W : 10, O : 8, C : 7, L : 5, M : 5,>
M	<W : 5, O, 6, C : 3, L : 4>
L	<W : 4, O, 3>
C	<W : 2, < O : 1>
O	<W : 1>

The next stage is to calculate the support value and also the confidence value, then sort the itemsets based on support and confidence, the next step is to determine the association rules from the values that have been obtained:

Table VIII

Combination of 2 itemsets

Item	***Qty***
O, W	14
C, W	11
L, W	12
M, W	11
T, W	13
C, O	6
L, O	10
M, O	13
T, O	10
L, C	7
M, C	7
C, T	8
M, L	9
T, L	8
T, M	7
C, W, O	6
L, W, O	8
M, W, O	7
T, W, O	10
L, W, C	7
M, C, W	7
T, W, C	8
M, W, L	8
L, W, T	8
M, W, T	7

Item	*Qty*
L, O, C	4
M,O, C	4
C, O, T	5
M, O, L	6
T, O, L	6
O, M, T	5
M, C, L	6
L, C, T	5
M, L, T	5

Table IX

Value of Minimum Amount of Support and Confidence

Item	*Qty*	*Support*	*Confidence*
O, W	14	46.67%	73.68%
C, W	11	36.67%	73%
L, W	12	40.00%	86%
M, W	11	36.67%	78,57%
T, W	13	43.33%	92.85%
C, O	7	23%	46.67%
L, O	10	33.33%	71.42%
M, O	11	36.67%	78.57%
T, O	10	33.33%	71.42%
L, C	7	23.33%	50.00%
M, C	7	23.33%	50.00%
C, T	9	30.00%	60.00%
M, L	9	30%	64.28%
T, L	8	26.67%	57.14%
T, M	7	23.33%	50%
C, W, O	6	20%	40.00%
L, W, O	8	26.67%	57.14%

Item	*Qty*	*Support*	*Confidence*
M, W, O	8	26.67%	57.14%
T, W, O	10	33.33%	71.40%
L, W, C	7	23.33%	50.00%
M, C, W	7	23.33%	31.81%
T, W, C	8	26.67%	36.36%
M, W, L	8	26.67%	36.36%
L, W, T	8	26.67%	36.36%
M, W, T	7	23.33%	50.00%
M,O, C	4	13.33%	28.57%
C, O, T	5	16.67%	33.33%
M, O, L	6	20%	42.85%
T, O, L	6	20%	42.85%
O, M, T	5	16.67%	33.33%
M, C, L	6	20%	43%
L, C, T	5	16.67%	35.71%
L, M, T	5	16.67%	35.71%
L, O, C	4	13.33%	21.52%

Support and confidence that will be used. The minimum support used in this research is 30% and the minimum confidence is 60%. The following is a table after determining the minimum support and confidence:

Table X

Minimum Support and Confidence Values

Item	*Qty*	*Support*	*Confidence*
O, W	14	46.67%	73.68%
C, W	11	36.67%	73%
L, W	12	40.00%	86%
M, W	11	36.67%	78,57%
T, W	13	43.33%	92.85%
L, O	10	33.33%	71.42%

Item	*Qty*	*Support*	*Confidence*
M, O	11	36.67%	78.57%
T, O	10	33.33%	71.42%
M, L	9	30%	64.28%
C, T	9	30.00%	60.00%

RESEARCH RESULT

From the stages that have been completed above, the items that meet the minimum confidence = 60% in Table 4.11 and conclusions can be drawn are as follows:

1. If a customer buys Bulk Cooking Oil (O) then the customer will also buy Chicken Eggs (W) with a support value = 46.67% and confidence = 73.68%
2. If a customer buys 1 KG Rice (C) then the customer will also buy Chicken Eggs (W) with support value = 36.67% and confidence = 73%
3. If a customer buys Bango Soy Sauce (L), the customer will also buy Chicken Eggs (W) with a support value = 40% and confidence = 86%
4. If a customer buys Instant Noodles (M) then the customer will also buy Chicken Eggs (W) with support value = 36.36% and confidence = 78.57%
5. If a customer buys Indofood Chili Sauce (T), the customer will also buy Chicken Eggs (W) with support value = 43.33% and confidence = 92.85%
6. If a customer buys Bangao Soy Sauce (L) then the customer will also buy Bulk Cooking Oil (O) with support value = 33.33% and confidence = 71.42%
7. If a customer buys Instant Noodles (M) then the customer will also buy Bulk Cooking Oil (O) with support value = 36.67% and confidence = 78.57%
8. If a customer buys Indofood Chili Sauce (T), the customer will also buy Bulk Cooking Oil (O) with a support value = 33.33% and confidence = 71.42%
9. If a customer buys Instant Noodles (M), the customer will also buy Bango Soy Sauce (L) with support value = 30% and confidence = 64.28%
10. If a customer buys 1 KG Rice (C) then the customer will also buy Indofood Chili Sauce (T) with a support value = 30% and confidence = 60.00%

CONCLUSION

Based on the design, analysis, implementation and testing of this research, the following conclusions can be drawn:

1. Overall, 34 rules were obtained from the sales sample data, consisting of 9 association rules that met the support threshold of 30% and 8 rules that met 70% confidence.
2. From the rules obtained, new knowledge is obtained about consumer purchasing patterns. This knowledge can be used to determine basic food supply decisions regarding purchasing patterns for products that have the highest confidence value.
3. The FP-Growth algorithm can help companies monitor the stock of goods that are frequently purchased by consumers so that there will be no shortage of merchandise.

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