Market Basket Analysis using FP-Growth Association Rule on Textile Industry

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Abstract Online shop is one of the technological developments that makes it easy for sellers and buyers to make transactions. A batch of data is produced from the process at an online shop and will be wasted if not utilized properly. An example is a batch of transaction data that may store hidden information that might benefit the online shop, such as information on customer transaction patterns or information on the relationship between two or more items that are most often purchased by customers. Based on that problem, this research conducts market basket analysis using one of the data mining methods, namely Association Rule with FP-Growth Algorithm, to find hidden information in a transaction data produced by an online shop. The data used in this research is an online shop transaction data that contains more than one item from November 2019 to December 2019 owned by one of the textile industries located in Ubud, Bali. The calculation of the FP-Growth Association Rule also tested using the Weka application. The results of market basket analysis are several associative rules related to the combination of best-selling items, such as "customers who buy Tigers Base Grey will have a 100% chance of buying Tribal Green too". The result can be utilized by the textile industry owner to manage the layout of the online shop, add item recommendation features to the online shop based on items purchased by the customer, and also keep stock of the best-selling items to prevent running out of stock.

***Index Terms*— Association Rule, Data Mining, FP-Growth, Market Basket Analysis, Weka**

I. Introduction

Online shop is one of the technological developments that makes it easy for sellers and buyers to make transactions [1]. The online shop allows sellers to sell goods through internet media such as websites or social media. Buyers can also choose the desired items through the website or social media, make payments by bank transfer, and receive goods without leaving the house. Nowadays, many brick-and-mortar businesses or industries are attracting more customers by opening online shops. That is because the online shop provides convenience that can be accessed by an internet connection anywhere and anytime. An example of the brick-and-mortar industry that started an online shop is one of the textile industries located in Ubud, Bali. A batch of data is produced from the process at an online shop and will be wasted if not utilized properly. An example is a batch of transaction data that may store hidden information that might benefit the online shop, such as information on customer transaction patterns or information on the relationship between two or more items that are most often purchased by customers. Therefore, market basket analysis can be applied to the transaction data using data mining methods to obtain hidden information [2].

Data mining, which can also be called knowledge discovery in a database, can be interpreted as an automated process of large amounts of data to find hidden relationships or patterns that might provide useful knowledge or information [3]–[6]. The Association Rule is one example of data mining methods used to find patterns or hidden information, such as information on the relationship between two or more items that most often appear simultaneously in a data set [7], [8]. The process to obtain information on the relationship between two or more items is known as market basket analysis in the business world [9].

This research applies the data mining Association Rule Method with the FP-Growth Algorithm to the transaction data of an online shop owned by one of the textile industries in Ubud, Bali, to obtain customer transaction patterns. The pattern obtained from the data mining process allows the owner of the textile industry to be able to manage the layout of the online shop site to be better, add feature recommendations to the online shop based on the items purchased by the customer, and keep stock of the best-selling items. This research performed data mining calculations manually as well as data mining using the Weka application and compared the final results of both.

II. LITERATURE REVIEW

A. Association Rule

The Association Rule Method is an example of a data mining method used to find patterns or hidden information, such as information on the relationship between two or more items that appear most frequently at the same time in a data set [7]–[11]. The Association Rule Method requires a minimum value for support and confidence. Items that have both support and confidence values under the specified conditions will be removed from the data set [12].

1. Support Value

The support value of an item indicates the frequency of an item in a transaction data set. The higher the support value, the more often the item appears in a data set [12].

2. Confidence Value

Confidence value shows the accuracy of the association rules between two or more items. The higher the confidence value, the higher the accuracy of the association rules between the two items [12]

The resulting association rules have a form of cause → effect, or antecedent → consequent, or if → then [13].

3. Lift Ratio

The lift ratio is used to evaluate the strength of the associative rule of two or more items. Lift ratio is the result of the confidence value of a rule divided by the benchmark confidence of that rule. Lift ratio values greater than 1 indicate the benefits of these rules. The higher the lift ratio value, the higher the strength of the associative rule [13].

B. FP-Growth

FP-Growth or Frequent Pattern Growth is one of the Association Rule Method algorithms that is used to find the combination of items that most often appear simultaneously in a data set [7], [8]. FP-Growth uses FP-Tree in determining the combination of items that most often appear in a data set [14]. FP-Growth algorithm consists of several stages as follows [15].

1. Frequent Item Discovery

The items that appear most often can be found by calculating the support value of each item in a data set. Items that have a support value below the minimum requirement of a support value will be removed from the data set, and those that have a support value that meets the requirements will be considered the items that appear most often and are further processed. The most frequently occurring items are sorted from highest frequency to lowest frequency in transaction data.

2. FP-Tree Construction

FP-Tree consists of several nodes, which are the most frequently occurring items in the transaction data. All items in the transaction data are inserted into the tree. Each item has a path value in the tree. A new branch will be created, if the prefix of the itemset is not yet available in the tree, otherwise, the path value for each item prefix is added by 1.

3. Frequent Itemset Discovery

The item combinations or itemset that appear most often can be found by analyzing the tree. The analysis is performed on every node in the tree and starts from the lowest node of the tree. The first step of the analysis is to determine the processed node. The next step is to change each node's path value of the same branch with the processed node to 0, except for the processed node. The next step is to trace the branches using the processed node through each node above it (the parent node) to the root node. Each time a processed node visits its parent node, the path value of the parent node is added by 1. The visit also results in a combination of items. If the processed node has reached the root node, then the path value of the processed node is reduced by 1. The process will end if the path value of the processed node has run out, and the currently processed node can be removed from the tree.

C. Weka

Weka is a data mining software for finding patterns or hidden information from a set of data that is the input value of the software. Weka supports several data mining methods, including the FP-Growth Association Rule. Weka provides easy data mining solutions and easy to use graphical user interface [7].

III. METHOD AND DATA

This research consists of several stages as follows.

A. Problem Identification

This stage discusses the background and problems that are the reasons for this research.

B. Literature Review

A literature review was conducted by finding references from related research that has been done. A literature review was conducted to support research activities.

C. Research Method and Data

This stage explains the flow of research as well as the data used in research.

D. Implementation and Result

This stage discusses the implementation and results of the FP-Growth Association Rule. The results obtained are the best-selling items as well as the best-selling item combinations at an online shop owned by one of the textile industries in Ubud, Bali.

E. Conclusion

This stage concludes the research that was conducted by taking the essence of the research.

F. Data

The data used in this research is an online shop transaction data that contains more than one item owned by one of the textile industries located in Ubud, Bali. The transaction period used is transactions from November 2019 to December 2019.

TABLE I
ITEM DATA

Item ID	Item Name
IM1	1 Colour Leaves
IM2	Banana Leaves (Navy)
IM3	Banana Leaves (Pink)
IM4	Big Banana Leaves (Blue)
IM5	Block Colour Stripe (Black)
IM6	Cactus (Tosca)
IM7	Fish (Blue)
IM8	Fish (Red)
IM9	Flamingo Light Pink
IM10	Flamingo Pink
IM11	Galaxy (Black and Yellow)
IM12	Galaxy (Grey)
IM13	Japanese Wave (Brown)
IM14	Leaves (Black)
IM15	Leaves (Blue Sky)
IM16	Leaves (Green)
IM17	Parrots (Red and Black)
IM18	Parrots (Yellow and Black)
IM19	Pineapple 3 Colours (Peach)
IM20	Rose Base Dark Green
IM21	Salur Small Black
IM22	Tigers Base Green
IM23	Tigers Base Grey
IM24	Tigers Base Peach
IM25	Tigers Light Pink Black
IM26	Tribal Green

Table 1 shows data of items sold through an online shop during the specified transaction period.

TABLE II
TRANSACTION DATA

Transaction ID	Items
IM1	IM6, IM7, IM13
IM2	IM12, IM10, IM11, IM8
IM3	IM2, IM3
IM4	IM2, IM3, IM4
IM5	IM5, IM1, IM17
IM6	IM15, IM16, IM14
IM7	IM24, IM19, IM18, IM20
IM8	IM9, IM21
IM9	IM25, IM22
IM10	IM26, IM23
IM11	IM23, IM26
IM12	IM24, IM26, IM18
IM13	IM18, IM20
IM14	IM9, IM21
IM15	IM26, IM23
IM16	IM10, IM11

Table 2 shows the combination of items sold in each transaction during the specified transaction period.

IV. IMPLEMENTATION AND RESULT

The FP-Growth Association Rule applied to the transaction data consists of several stages, namely frequent item discovery, FP-Tree construction, frequent itemset discovery, association rule discovery, and lift ratio calculation.

A. *Frequent Item Discovery*

This stage performs a process to find the best-selling items (frequent items) during the specified period by calculating the support value of each item using the following equation [12].

$$Support(A) = \frac{\sum transactions\ with\ item\ A}{\sum transactions}$$

The equation divides the number of occurrences of an item by the total number of transactions. An example of applying the equation is calculating support value for item IM1.

$$Support(IM1) = \frac{1}{6} = 0.0625$$

Item IM1 only appears once, namely in Transaction T5, and then divided by the total number of transactions, which is 16, and produces a support value of 0.0625. The calculation is performed on each item and continued by determining the minimum support value. The minimum support value for frequent items used in this research is 0.1, which means that only items that have a support value of more than 0.1 will be further processed.

TABLE III
SUPPORT VALUE OF FREQUENT ITEMS

Item ID	Frequency	Support
IM1	4	0.25
IM2	3	0.1875
IM3	3	0.1875
IM4	2	0.125
IM5	2	0.125
IM6	2	0.125
IM7	2	0.125
IM8	2	0.125
IM9	2	0.125
IM10	2	0.125
IM11	2	0.125

Table 3 shows items that have a support value more than the specified minimum support value. The items in table 3 are sorted by frequency from the largest to the smallest. This process shows the best-selling items, namely IM26 (Tribal Green). The next stage is altering the transaction data by eliminating items that do not meet the minimum support value.

TABLE IV
TRANSACTION DATA WITH FREQUENT ITEMS

Transaction ID	Items
T2	IM10, IM11
T3	IM2, IM3
T4	IM2, IM3
T7	IM18, IM20, IM24
T8	IM9, IM21
T10	IM26, IM23
T11	IM26, IM23
T12	IM26, IM18, IM24
T13	IM18, IM20
T14	IM9, IM21
T15	IM26, IM23
T16	IM10, IM11

Table 4 shows the transaction data that has been altered, which only contains items that meet the minimum support value. Items in transaction data are also sorted by frequency from the largest to the smallest.

B. *FP-Tree Construction*

FP-Tree consists of a root node and several branches that contain nodes. Each row of the transaction data is represented as a branch that contains several nodes, which represent each item in transaction data.

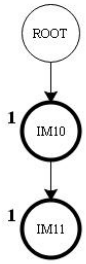

Fig. 1. Transaction T2 in a form of FP-Tree.

Figure 1 shows the FP-Tree branch that was generated from transaction T2 consisting of IM10 and IM11 nodes. The path value at the top-left point of the node shows the number of the node being visited. Each node in this branch has a path value of 1.

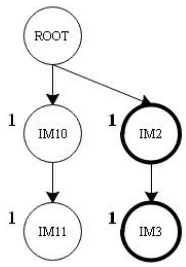

Fig. 2. Transaction T3 in a form of FP-Tree.

Figure 2 shows the FP-Tree branch that was generated from transaction T3 consisting of IM2 and IM3 nodes. This stage generates a new branch from the root node because there are no branches beginning with the IM2 node. Each node in this branch has a path value of 1.

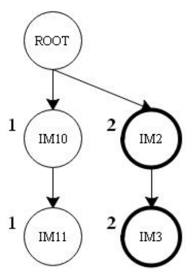

Fig. 3. Transaction T4 in a form of FP-Tree.

Figure 3 shows the FP-Tree branch that was generated from transaction T4 consisting of IM2 and IM3 nodes. This stage does not generate a new branch, because a branch with the IM2 node followed by the IM3 node is already available in the tree. Therefore, the path value of the IM2 and IM3 node is added by 1.

Figure 4 shows the FP-Tree branch that was generated from transaction T7 consisting of IM18, IM20, and IM24 nodes. This stage generates a new branch from the root node because there are no branches starting with the IM18 node. Each node in this branch has a path value of 1.

The process continues until all transaction data is converted to FP-Tree. The final result of the FP-Tree constructed using transaction data with frequent items is presented in Figure 5.

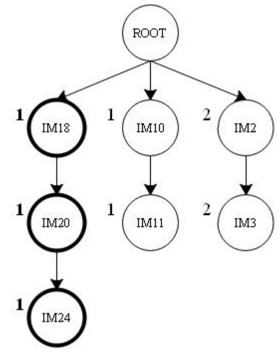

Fig. 4. Transaction T7 in a form of FP-Tree.

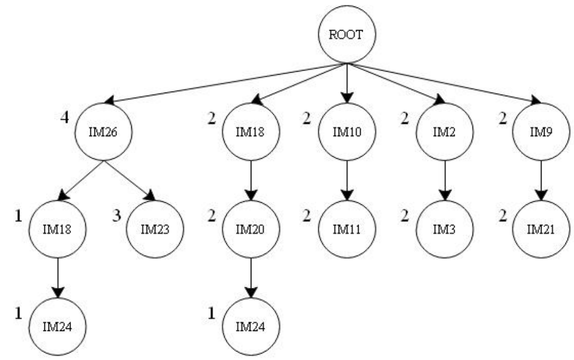

Fig. 5. Final result of FP-Tree.

C. *Frequent Itemset Discovery*

The next stage is finding the frequent itemset or combinations of best-selling items that are purchased together. Frequent itemset are discovered by analyzing each node in a branch of the generated FP-Tree. The process starts with the lowest node in the FP-Tree.

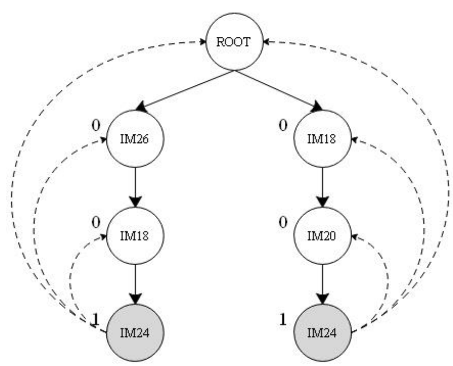

Fig. 6. Frequent itemset discovery process of IM24.

An example of the node to be processed is the IM24 node. Figure 6 shows the FP-Tree that focuses on branches that have IM24 node and is used to discover the combination of items that are most often purchased simultaneously with IM24. The first step is to change each node's path value to 0, except for the IM24 node. The next step is to trace the branch using the IM24 node through each node above it (the parent node) to the root node. Each time IM24 visits a parent node, the path value of the parent node is added by 1. A combination also generated when the IM24 node visits a parent node, for example, the combination of {IM24, IM18}.

If the IM24 node has reached the root node, then its path value is reduced by 1. The process will stop if the path value of the IM24 node has run out, and the IM24 node at the current branch can be removed from the tree.

Based on the example, the items that most frequently bought with IM24 are {IM24} itself as well as a combination of {IM24, IM18}, {IM24, IM26}, {IM24, IM20}, and {IM24, IM18}. Items that do not have a combination with other items can be removed, and also combinations o f {IM24, IM26} and {IM24, IM20} can be removed because those combinations appear only once. Combinations that appear more than once can be written once. Therefore, the frequent itemset discovered in this process is {IM24, IM18}.

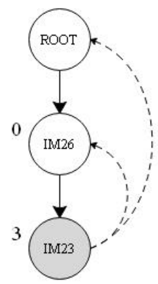

Fig. 7. Frequent itemset discovery process of IM23.

Another example of the node to be processed is the IM23 node. Figure 7 shows the FP-Tree that focuses on a branch that has IM23 node and is used to discover the combination of items that are most often purchased simultaneously with IM23. The process is the same as before, namely change each node's path value to 0, except for the IM23 node. Trace the branch using the IM23 node through each node above it (the parent node) to the root node until the path value of the IM23 node has run out, and the IM23 node at the current branch can be removed from the tree.

Based on the example, the items that most frequently bought with IM23 are {IM23} itself as well as a combination of {IM23, IM26}, {IM23, IM26}, and {IM23, IM26}. The frequent itemset discovered in this process is {IM23, IM26}.

TABLE V
FREQUENT ITEMSET

Item ID	Itemset
IM18	{IM18, IM26}
IM23	{IM23, IM26}
IM3	{IM3, IM2}
IM11	{IM11, IM10}
IM20	{IM20, IM18}
IM21	{IM21, IM9}
IM24	{IM24, IM18}

Table 5 shows the frequent itemset or combination of items that are most often purchased together. The next step is to determine the support value of each frequent itemset [12]

$$Support(A \cap B) = \frac{\sum transactions\ with\ item\ A\ \&\ B}{\sum transactions}$$

The equation divides the frequency of occurrence of a combination of items or itemset with the total number of transactions. An example of applying this equation is to calculate the support value itemset {IM18, IM26}.

$$Support(IM23 \cap IM26) = \frac{1}{16} = 0.0625$$

Itemset {IM18, IM26} only appears once, namely in Transaction T12, and then divided by the total number of transactions, which is 16, and produces a support value of 0.0625. Calculations are performed on each frequent itemset. The minimum support value also applies at this stage, where the minimum support value for frequent itemset is the same as minimum support value for frequent items, namely 0.1.

TABLE VI
SUPPORT VALUE OF FREQUENT ITEMSET

Frequent Itemset	Support
{IM23, IM26}	0.1875
{IM3, IM2}	0.125
{IM11, IM10}	0.125
{IM20, IM18}	0.125
{IM21, IM9}	0.125
{IM24, IM18}	0.125

Table 6 shows itemset that have a support value more than the specified minimum support value.

D. *Association Rule Discovery*

The next stage after frequent itemset was discovered is to calculate the confidence value for each frequent itemset that meets the minimum support value [12].

$$Confidence(A|B) = \frac{\sum transactions\ with\ item\ A\ \&\ B}{\sum transactions\ with\ item\ A}$$

The equation divides the frequency of occurrence of the combination of item A and item B with the number of transactions containing item A. An example of applying the equation is to calculate the confidence value of the itemset {IM23, IM26}.

$$Confidence(IM23|IM26) = \frac{3}{3} = 1$$

Itemset {IM23, IM26} appears 3 times, namely in Transaction T12, T11, as well as T16. The number then divided by the total number of transactions containing IM23. Transactions T10, T11, and T15 contain IM23, thus, resulting in a confidence value of 1 for the itemset {IM23, IM26}. This stage also defines the minimum confidence value to eliminate the itemset that does not meet the minimum confidence value. The minimum confidence value used in this research is 0.9.

TABLE VII
ASSOCIATION RULES

Frequent Itemset	Association Rule	Confidence
{IM23, IM26}	IM23 → IM26	1
{IM3, IM2}	IM3 → IM2	1
{IM11, IM10}	IM11 → IM10	1
{IM20, IM18}	IM20 → IM18	1
{IM21, IM9}	IM21 → IM9	1
{IM24, IM18}	IM24 → IM18	1

Table 7 shows the association rule formed from frequent itemset that meets minimum confidence value.

E. *Lift Ratio Calculation*

The lift ratio is obtained from the confidence value of a rule divided by the benchmark confidence value of the same rule. Benchmark confidence can be calculated using the following equation [13].

$$Bench.Conf.(A|B) = \frac{\sum transactions\ with\ item\ B}{\sum transactions}$$

An example of applying the equation is to calculate the benchmark confidence value of the association rule IM23 → IM26.

$$Bench.Conf.(IM23|IM26) = \frac{4}{16} = 1$$

Item IM26 appears 4 times, namely in Transaction T10, T11, T12, as well as T15. The number then divided by the total number of transactions, which is 16. Therefore, resulting in the benchmark confidence of 0.25 for itemset IM23 → IM26. After the benchmark confidence of a rule is obtained, the lift ratio can be calculated with the following equation [13].

$$Lift\ Ratio = \frac{Coonfidence}{Benchmark\ Confidence}$$

An example of applying the equation is to calculate the lift ratio of the association rule IM23 → IM26.

$$Lift\ Ratio = \frac{1}{0.25} = 4$$

The lift ratio for the association rule IM23 → IM26 is 4, which is higher than 1. That means the association rule has good strength and benefits.

TABLE VIII
ASSOCIATION RULES

Association Rule	Confidence	Benchmark Confidence	Lift Ratio
IM23 → IM26	1	0.25	4
IM3 → IM2	1	0.125	8
IM11 → IM10	1	0.125	8
IM20 → IM18	1	0.1875	5.3
IM21 → IM9	1	0.125	8
IM24 → IM18	1	0.1875	5.3

Table 8 shows the association rules with its confidence, benchmark confidence, and lift ratio value.

F. Weka

Weka is an application that can be used to do data mining without manual calculations. Weka has a library to be able to mine data using the Association Rules Method with the FP-Growth Algorithm. The library is used to extract hidden patterns or information from an online shop transaction data that contains more than one item in a specified transaction period owned by one of the textile industries located in Ubud, Bali.

```
-P 2 -I -1 -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
```

Fig. 8. Weka settings.

Figure 8 shows the settings of the FP-Growth Association Rule in Weka. The -C code is the minimum confidence value set to 0.9 and the -M code is the minimum support value set to 0.1.

Figure 9 shows the results of the FP-Growth Association Rule on transaction data using the Weka application. The results obtained through manual calculations, as shown in Table 8, have no difference with the results obtained using the Weka application.

```
=== Associator model (full training set) ===

FPGrowth found 9 rules (displaying top 9)

1. [IM23=Y]: 3 ==> [IM26=Y]: 3   <conf:(1)> lift:(4) lev:(0.14) conv:(2.25)
2. [IM24=Y]: 2 ==> [IM18=Y]: 2   <conf:(1)> lift:(5.33) lev:(0.1) conv:(1.63)
3. [IM20=Y]: 2 ==> [IM18=Y]: 2   <conf:(1)> lift:(5.33) lev:(0.1) conv:(1.63)
4. [IM9=Y]: 2 ==> [IM21=Y]: 2   <conf:(1)> lift:(8) lev:(0.11) conv:(1.75)
5. [IM21=Y]: 2 ==> [IM9=Y]: 2   <conf:(1)> lift:(8) lev:(0.11) conv:(1.75)
6. [IM3=Y]: 2 ==> [IM2=Y]: 2   <conf:(1)> lift:(8) lev:(0.11) conv:(1.75)
7. [IM2=Y]: 2 ==> [IM3=Y]: 2   <conf:(1)> lift:(8) lev:(0.11) conv:(1.75)
8. [IM11=Y]: 2 ==> [IM10=Y]: 2   <conf:(1)> lift:(8) lev:(0.11) conv:(1.75)
9. [IM10=Y]: 2 ==> [IM11=Y]: 2   <conf:(1)> lift:(8) lev:(0.11) conv:(1.75)
```

Fig. 9. FP-Growth Association Rule results using Weka.

A probability will be generated if the confidence value is multiplied by 100%. An example is the confidence value for the association rule IM23 → IM26 which is 100%. That means "customers who buy IM23 (Tigers Base Grey) will have a 100% chance of buying IM26 (Tribal Green) too". That statement is an association rule generated through the process of data mining in an online shop transaction data that contains more than one item in a specified transaction period owned by one of the textile industries located in Ubud, Bali.

V. CONCLUSION

Online shop is one of the technological developments that makes it easy for sellers and buyers to make transactions that produce a batch of transaction data. Market basket analysis can be done by applying data mining methods to the transaction data to determine the shopping patterns of customers. Data mining was conducted in this research using the FP-Growth Association Rule to the transaction data of an online shop owned by one of the textile industries located in Ubud, Bali. to obtain customer transaction patterns. Transaction data used in this research is transaction data containing more than one item in the textile industry's online shop from November 2019 to December 2019.

The FP-Growth association rule consists of several stages, namely frequent item (support items) discovery, FP-Tree construction, frequent itemset (support itemset) discovery, association rules discovery, and lift ratio calculation. The Weka application is also used to perform data mining calculations faster. The results of data mining obtained from manual calculations and the Weka application in this research have no difference. One example of these results is the association rule IM23 → IM26 which shows the statement that "customers who buy IM23 items (Tigers Base Grey), then have a 100% chance will also buy IM26 items (Tribal Green)". In addition, through data mining using the FP-Growth Association Rule, the most frequently sold items, namely IM26 (Tribal Green) items are also obtained. The benefit of knowing these patterns or rules is that the textile industry owner can manage the layout of the online shop, add item recommendation features to the online shop based on items purchased by the customer, and also keep stock of the best-selling items to prevent running out of stock.

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