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COMPARISON BETWEEN APRIORI AND FP-GROWTH ALGORITHMS ON INVENTORY MODEL OF ITEM AVAILABILITY

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Abstract

In this study, it will be discussed the comparison between apriori and fp-growth algorithms on an inventory model of item availability. The research about this topic becomes important and interesting to be studied because it illustrates the implementation of applied mathematics by constructing the matematical model, namely an inventory model of item availability. Then, the model will be solved by using apriori and fp-growth algorthms related to the application of probability theory. In this case, apriori and fp-growth algorithms are used to specify
the pattern of dependency relationships between an item and other items so that the probability of item purchase based on other goods can be discovered. Moreover, the number of items which should be provided by a seller in a shop or a supermarket can be calculated. In order to figure out the output of this research which is the analysis of the comparison between apriori and fp-growth algorithms on the inventory model of item availbility, then choosing and categorizing kinds of items based on the sales, using the apriori and fp-growth algorithms, constructing the model, solving and interpreting it are established.

Keywords: *Mathematical modeling, probability, apriori algorithm, fp-growth algorithm.*

INTRODUCTION

Along with the development of competition in the business world, especially in the sales industry, a businessman is required to find a strategy that can increase sales and marketing of sold products/items. Before the strategy is designed, it is necessary to continuously analyze the sales results within a certain period. This is intended to ascertain how much an increase in sales occurs. Sales increase can be attempted as much as possible by looking at the relationship of dependence on the sale of the item with other items. For example, if a consumer buys a toothbrush, then the consumer will also certainly buy toothpaste. By observing the trend pattern of purchasing an item depending on the sale of other items, business people can make a strategy by providing both item stocks in the same quantity for each interdependent item. In addition, in order to make the maximum sales and increase profits, business people can also put these items together in a container with promised price cuts so that all items can be sold at the same time.

Such a problem above can be considered as a mathematical modeling. Mathematical modeling is one of the branches of applied

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mathematics commonly used by mathematicians in predicting a variable or condition in the future. Therefore, to predict how much the sales will increase in the future and the probability of item purchase depends on the sale of other items, it is necessary to construct a mathematical model, namely an inventory model of item availability.

The solution of the mathematical model uses apriori algorithm to determine the relationship pattern of the dependence between an item and other items in the sales transaction data. A priori algorithm is too important to analyze the transaction data and help customers in buying the items they want more easily such that the sales can be risen. This algorithm has been used in various problems, such as A. Nursikuwagus and T.Hartono [2] used the algorithm for analyzing sales with web based and Kuo M.H, Kusniruk A.W, Borycki E.M, & Greig D [6] utilized it for detection of adverse drug reaction. In addition, Not only did L.Hakim and A.Fauzy [8] apply the same algorithm for determining the pattern of traffic accidents, but also Pria Nita and RB Fajriya Hakim [10] applied it for analyzing the data pattern of aircraft accidents. Besides, Christian Bolgelt & Otto von Guericke [13] have discussed about an implementation of the FP-Growth Algorithm. In addition, Kumar B.S & Rukmani K.V [14] studied about implementation of web usage mining using Apriori and FP-Growth Algorithms. In this paper the comparison betwen apriori and fp-growth algorithms is given for analyzing the sales transaction data to construct an inventory model of items availability.

LITERATURE REVIEWS

In this section some reviews about set theories, probabilities, apriori and fp-growth algorithms will be discussed.

Set Theories

The following is given some definitions related to the sets and several operations on the sets.

Definition [3] *A set* is a collection of objects which are unordered and no repetition determined by its elements/members and usually represented by a capital letter. *Elements* of a set are the objects in the collection.

Suppose that x is an element of a set A. Then, it can be written as $x \in A$. The number of elements in the set A is called a cardinality of A, denoted by $\#A$.

Definition 2.1.2 [3] Given A and B are two sets. A is *a subset* of B, written as $A \subset B$ if and only if every element of A is an element ofi B. A is *a proper subset* of B if and only if $A \subset B$ and $A \neq B$. A is a subset of B, denoted by $A \subseteq B$ if and only if $A \subset B$ dan $A = B$.

There are several operations on sets as follows:

1. Union

The union of two sets A dan B is the set

$$A \cup B = \{x \mid x \in A \text{ or } x \in B\}.$$

In a form of a Venn diagram, it can be illustrated as

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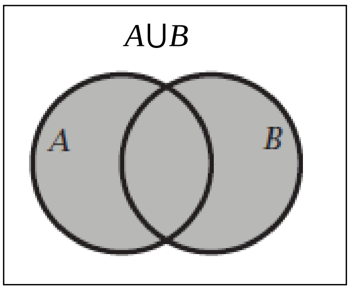

Figure 1. A union of two sets

Intersection

The intersection of two sets A dan B is the set

$A \cap B = \{x \mid x \in A \text{ and } x \in B\}$.

In a form of a Venn diagram, it can be depicted as

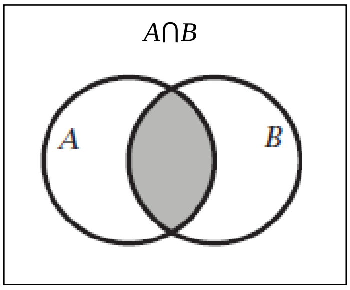

Figure 2 An intersection of two sets

Probabilities

The set of all possible results from an experiment is called *a sample space*, denoted by Ω, while *an event* is a subset of the sample space Ω [8].

Definition [9] Events $A_1, A_2, \ldots$ are called as *disjoint events* if $A_i \cap A_j = \emptyset, i \neq j$.

Definitio [9] For an experiment, Ω expresses the sample space and $A_1, A_2, \ldots$ are possible events of the experiment. A set function that relates the real value $P(A)$ with each event is called *a probability set function* and $P(A)$ is called the probability of the event A, if the following properties are met:

1. $0 \le P(A) \le 1, \forall A,$
2. $P(\Omega) = 1,$
3. $P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$ if $A_1, A_2, \ldots$ are disjoint.

Definition [9] Two events A and B are *independent* if and only if

$$P(A \cap B) = P(A)\,P(B). \quad (2.1)$$

Otherwise, two sets A and B are called as *dependent events.*

Definition 2.2.4 [9] *A conditional probability* of the event B if given the event A has occured, is as follows:

$$P(B \mid A) = \frac{P(A \cap B)}{P(A)}, P(A) > 0. \quad (2.2)$$

Apriori Algorithm

Apriori algorithm was first developed by Agrawal and Srikant in 1994. It is an innovative way to find association rules on large scale allowing implication outcomes that consist of more than one item. The algorithm uses a generate and test approach which means that it generates candidate itemsets and test if they are frequent. The following will be given some definitions and explanation related to the apriori algorithm.

An itemset is a set of items that occur together. *Association rule* is a rule that shows a probability of particular items which are purchased together.

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For an example, the rule {bread, butter} $\Rightarrow$ {jam} found in the sales data of a supermarket would indicate that if a customer buys bread and butter together, they are likely to also buy jam. Such information can be used as the basis for decisions about marketing activities such as e.g. promotional pricing or product placement.

Support of an item X, denoted by supp(X) is the ratio of transactions in which an itemset appears to the total number of transactions.Moreover, the *support count* of an item X is the frequency or the total number of the item which appears in all transaction. Itemsets that meet a minimum support threshold are referred to as *frequent itemsets*.*Confidence* is the occurence of goods; the chances of an item X happening given an item Y has already happened. On the other hand, confidence measure how often goods in Y appear in transactions that contain X.
Confidence of rule $X \Rightarrow Y$ denoted by $\mathrm{conf}(X \Rightarrow Y)$ is given as follows.

$$\mathrm{conf}(X \Rightarrow Y) = \frac{\mathrm{supp}(X \cup Y)}{\mathrm{supp}(X)}. \qquad (2.3)$$

Confidence can also be defined in terms of the conditional probability namely

$$\mathrm{conf}(X \Rightarrow Y) = P(Y \mid X) = \frac{P(X \cap Y)}{P(X)}.$$

The apriori principle says that any subset of a frequent itemset must be frequent. The procedures of apriori algorithm are the following:

1. Given data in the database in regard to sales transaction data.
2. Set the minimum support.
3. Calculate the support or frequency of all items.
4. Discard the items with the support which is less than minimum support.
5. Combine two items and count their support.
6. Go back to step 4.
7. Combine three items and count their support.
8. Go back to step 4.
9. Stop if there is no possible combination.

Then, apriori algorithm can be illustrated as follows.

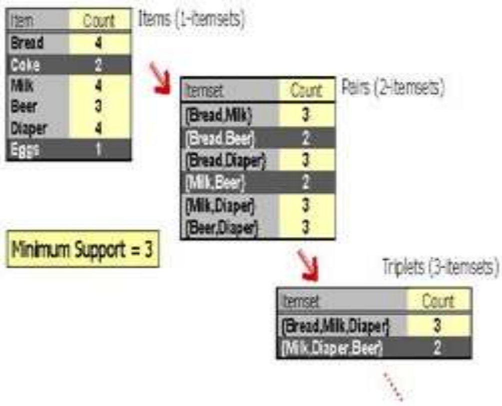

Figure 3. Illustration of Apriori Algorithm

2.4 FP-Growth Algorithm

FP (Frequent Pattern)-Growth algorithm is the common used algorithm that allows frequent itemset discovery without candidate itemset generation. Here a compact data structure called FP-Tree is built and frequent itemsets are directly extracted from the FP-Tree. The algorithm is given in the following steps.

a. Set the minimum support.
b. List the items and their support counts.
c. Sort the items in descending order
d. Generate fp-tree in which the root of the tree is null.
e. Determine conditional base pattern by starting from the node with minimum support and excluding the node with maximum support.

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RESEARCH METHODS

In this section, it will be given the steps that have been done during the reseach period as follows.

1. Preliminary research, includes literature study related to the research topic.
2. Taking data, which is sales transaction data from a minimarket; Minang Mart.
3. Choosing and classifying the types of items based on the sales transaction data.
4. Using apriori algorithm, namely
   a. Set the minimum number of items in all transactions (minimum support).
   b. Calculate the number of items from sales results (support count).
   c. Calculate the probability precentage of those appeared items.
   d. Construct the group combination of the possible items and calculate the support and its percentage.
5. Using fp-growth algorithm, namely
   f. Set the minimum support.
   g. List the items and their support counts.
   h. Sort the items in descending order
   i. Generate fp-tree in which the root of the tree is null.
   j. Determine conditional base pattern by starting from the node with minimum support and excluding the node with maximum support.
6. Constructing an inventory model of items availability.
7. Solving the model.
8. Interpretating the solution of the model.

4. DISCUSSION AND RESULTS

In this section, the comparison between apriori and fp-growth algorithms will be discussed as follows. First, the sales transaction data will be used to see the trend pattern of purchase an item based on the sale of other items. Then, it becomes a reference to analyze the products which should be supplied. The description about apriori and fp-growth algorithms will be explained in the example below.

Given the sales transaction data *D* in the table below.

TID	Itemsets
1	sugar, butter, eggs
2	jam, butter, bread
3	sugar, bread, jam, butter
4	bread, jam
5	fruit

Table 1. Sales Transaction Data

This table shows the puchase of itemsets for each 5-transaction. This data can be stated as a binary *m*x*n* binary matrix as follows.

TID	*A*	*B*	*C*	*D*	*E*	*F*
1	0	0	1	0	1	1
2	0	1	1	1	0	0
3	0	1	1	1	0	1
4	0	1	0	1	0	0
5	1	0	0	0	0	0

Table 2. Sales Transaction Data

In table 2, TID refers to a transaction identity. There are 5 transactions chosen and 6 items bought, namely *A*, *B*, *C*, *D*, *E*, and *F*. Let *A* be fruit, *B* be bread, *C* be butter, *D* be jam, *E* be eggs, and *F* be sugar. The binary matrix above has the value of 1 whenever the item is bought and otherwise 0. Next, given the minimum support is 40% with the support count of 2. So every itemset is a valid candidate appearing at least in two out of 5 transactions. At each iteration, the support of candidate itemsets is calculated eliminating those which support is under the threshold. Thus, the support for 1-itemsets from the data shown in Table 4.2 is counted in the following table.

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1-itemsets	Support Count (SC)	Support
$\{A\}$	1	0,2
$\{B\}$	3	0,6
$\{C\}$	3	0,6
$\{D\}$	3	0,6
$\{E\}$	1	0,2
$\{F\}$	2	0,4

Table 3. 1-itemsets with their support

The itemsets $\{A\}$ and $\{E\}$ are discarded in this table because the support does not meet the minimum support threshold. So, there are 4 items, namely B, C, D and F that will be used for the next step. In addition, the combination of 2-itemsets among these goods will yield 6 possible combinations which is

$$C(4,2)! = 4!/[2!(4-2)!]= 24/(2*2)=6.$$

Note that it can be obtained using the formula

$$C(n,r) = \frac{n!}{r!(n-r)!} \quad (4.1)$$

which is the total number of all possible combinations for choosing r elements at a time from n distinct elements without considering the order of the elements. Among these combination, the support will be calculated in the table as follows.

2-itemsets	SC	Support
$\{B, C\}$	2	0,4
$\{B, D\}$	3	0,6
$\{B, F\}$	1	0,2
$\{C, D\}$	2	0,4
$\{C, F\}$	2	0,4
$\{D, F\}$	1	0,2

Table 4. 2-itemsets with their support

In Table 4, there are four combinations which have satisfied the minimum support since $\{B, F\}$ and $\{D, F\}$ do not meet the minimum support. Moreover, the combination of 3-itemsets among 4 items will give 4 possible combinations and their support can be given in the following table.

3-itemsets	SC	Support
$\{B, C, D\}$	2	0,4
$\{B, C, F\}$	1	0,2
$\{B, D, F\}$	1	0,2
$\{C, D, F\}$	1	0,2

Table 5. 3-itemsets with their support

Table 5 leaves the only one combination that meets the minimum support threshold summarized in the table below.

3-itemsets	SC	Support
$\{B, C, D\}$	2	0,4

Table 6. Final frequent itemsets

Using the result in table 6, the possible association rules with their support and confidence can be calculated using the formula in (2.3) as follows.

Association rules	Support	Confidence
$\{B\} \Rightarrow \{C, D\}$	40%	67%
$\{C\} \Rightarrow \{B, D\}$	40%	67%
$\{D\} \Rightarrow \{B, C\}$	40%	67%
$\{C, D\} \Rightarrow \{B\}$	40%	100%
$\{B, D\} \Rightarrow \{C\}$	40%	67%
$\{B,C\} \Rightarrow \{D\}$	40%	100%

Table 7. The possible association rules

From the table 7, by setting the minimum confidence is at least 70 %, it is chosen the best association rules, namely
1. $\{C, D\} \Rightarrow \{B\}$.
2. $\{B, C\} \Rightarrow \{D\}$.

The rule $\{C, D \Rightarrow \{B\}$ will indicate that if people buy butter (C) and jam (D), then they will buy bread (B) with the confidence of 100%. However, if they buy bread, then they will buy butter and jam with the confidence of 67%. Furthermore, the rule will state that if people buy bread and butter, then they will buy jam with the confidence of 100%. In contrast, if they buy jam, then they will buy bread and butter with the confidence of 67%. In this case, the items which are bread,

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butter, and jam should be put together so that their position is closed each other. Moreover, these items should be supplied in the same amount.

Now, the previous example will be solved by using fp-growth algorithm as follows. First, calculating the support count for 1-itemsets is done the same as apriori algorithm seen in Table 4.3. Since The itemsets {*A*} and {*E*} are discarded, there are four items left for the next step. Second, these items will be sorted in descending order based on their support count. The result is given in the following table.

Items	Support Count (SC)
{*B*}	3
{*C*}	3
{*D*}	3
{*F*}	2

Table 8. Items in Descending order

Based on this table, Table 8 will be stated in descending order as follows.

TID	Itemsets	Ordered Itemsets
1	sugar, butter, eggs	butter (*C*), sugar (*F*)
2	jam, butter, bread	bread (*B*), butter (*C*), jam (*D*)
3	sugar, bread, jam, butter	bread (*B*), butter (*C*), jam (*D*), sugar (*F*)
4	bread, jam	bread (*B*), jam (*D*)
5	fruit	-

Table 9. Sales Transaction Data in Order

Table 4.9 shows that the last transaction does not exist anymore since there is only one item in it where the item has been excluded from the item list. So there are 4 transactions left to be considered further.

After that, the fp-tree will be generated by using this result. Starting from the root of tree is null, a path from *C* to *F* based on the first transaction. Then, the second transaction is represented by a path from *B* to *D* through *C*. Futhermore the third one passes the same path as the second one but it goes further and ends in the node *F*. Finally, the last one also forms the new path which passes the same node *B* but it stops in the node *D*. So the fp-tree can be illustrated as follows.

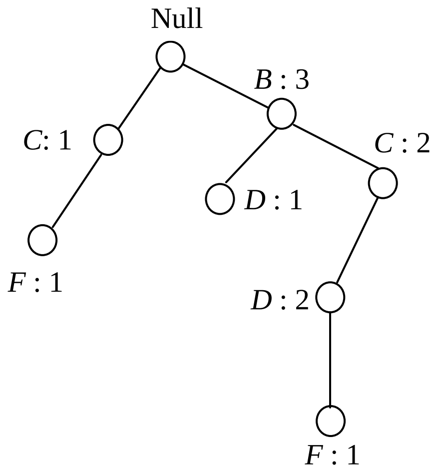

Figure 3. FP-Tree

Next, the last step to do is determining the conditional base pattern. In this step, two things should be done. First, starting from the node with the minimum support which is *F*. Then, Exluding the node with the maximum support which is *B*. The result in this step can be seen the following table.

Items	Conditional Pattern Base	Conditional FP-Tree	Frequent Patterns Generated
F	{*C*: 1}, {*B*,*C*,*D* : 1}	$\{\cancel{C:1}\}$, $\{\cancel{B:1}\}$, $\{\cancel{C:1}\}$, $\{\cancel{D:1}\}$	None
D	{ *B*, *C* : 2}, {*B* : 1}	{*B* : 3}, {*C* : 2}	{ *B*, *C* : 2} { *B*, *C*, *D* : 2}
C	{ *B* : 2}	{ *B* : 2}	{ *B*, *C* : 2}

Table 10. Conditional Base Pattern

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Figure 3 and Table 10 describe the paths exist in the fp-tree. There are two paths going to *F* in the column of conditional pattern base (starting from the different nodes, *C* and *B*), namely{*C*, *F*} written as {*C*: 1} with SC = 1and{*B*, *C*, *D*, *F*} written as {*B*,*C*,*D* : 1} with SC = 1. These paths cannot be used for the next two colums because they do not meet the minimum support of 2. In this case, there is no frequent patterns generated. Next, there are also two paths going to *D* and starting from the same node, *B*. They are { *B*, *C*, *D*} written as { *B*, *C* : 2} with SC = 2 and and {*B*, *D*} written as {*B* : 1}. Then, the conditional fp-trees are {*B* : 3} and {*C* : 2} getting from the column of the conditional pattern base. Thus, in the last column, it yields { *B*, *C* : 2}. This means that the frequent pattern generated is { *B*, *C*, *D* : 2} with SC = 2. Finally there is only one path going to C which is { *B*, *C*} written as { *B* : 2} with SC = 2 so that the frequent pattern generated is { *B*, *C* : 2} with SC = 2.

Note that fp-growth algorithm in Table 4.10 gives the same result as apriori algorithm in Table 4.6, which is{ *B*, *C*, *D* } so that the same association rules are found as before in apriori algorithm. By using these two algorithms in the previous example, it can be concluded that fp-growth algorithm is easier than apriori algorithm. The fp-growth requires less time to solve the problem. The comparison between these two algorithm can be summarized in the table below.

	Apriori Algorithm	FP-Growth Algorithm
Space	requires more space	requires less space
time	needs more computation time	needs less computation time
memory	uses most of memory	Uses less memory
Number of Scan	scan each candidate in itemsets	scan only two candidates

Table 11. Comparison between Apriori and FP-Growth Algorithms

Therefore, fp-growth algorithm is better than apriori algorithm so that it is recommended for improving the apriori algorithm.

Based on the example above, the inventory model can be constructed as follows. Given the database *D* which is sales transaction data consisting of events $T_1, T_2, \ldots, T_m$. Then, *D* can be written as $D = \{ T_1, T_2, \ldots, T_m \}$. Suppose that there is the *n*-th itemset X_n , namely a subregion of the event T_m, which is $X_n \subseteq T_m$. The database *D* can be written as a binary matrix with the size of *m*x*n* in which

$$X_n = \begin{cases} 1, \text{if the item is bought} \\ 0, \quad \text{otherwise.} \end{cases} \tag{4.2}$$

So the inventory model can be represented as a binary *mxn* matrix as D_{mxn} with the confidence defined as

$$\operatorname{conf}(X_a \Rightarrow X_b) = \frac{\operatorname{supp}(X_a \cup X_b)}{\operatorname{supp}(X_a)} \tag{4.3}$$

or

$$\operatorname{conf}(X_a \Rightarrow X_b) = P(X_b \mid X_a) = \frac{P(X_a \cap X_b)}{P(X_a)}.$$

Next, from that model, the assosiation rule $X_a \Rightarrow X_b$ would like to be found such that X_a and X_b are the subregions of event T_m, that is

$$X_a \subseteq T_m \wedge X_b \subseteq T_m$$

in which $X_a \cap X_b = \emptyset$.

Now, the model will be solved for the previous example. Suppose that $D = \{ T_1, T_2, T_3, T_4, T_5 \}$ in which there are 5 goods available, that is $X = \{ X_1, X_2, X_3, X_4, X_5, X_6 \}$. Let $T_1 = \{0,0,1,0,1,1\}$, $T_2 = \{0,1,1,1,0,0\}$, $T_3 = \{0,1,1,1,0,1\}$, $T_4 = \{0,1,0,1,0,0\}$, and T_5

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= {1,0,0,0,0,0}. So the inventory model D is a binary 5x6 matrix, namely

$$D_{5x6} = \begin{pmatrix} 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Then, using apriori algorithm will yield the association rule as follows.
1. $\{X_3, X_4\} \Rightarrow \{X_2\}$.
2. $\{X_2, X_3\} \Rightarrow \{X_4\}$.

The first rule means that if people buy X_3 and X_4, then they will buy X_2 with the confidence of 100%. Furthermore, the second rule indicates that if people buy X_2 and X_3, then they will buy X_4 with the confidence of 100%. However, these two rules do not hold in another way around.

Using the same way as the previous example, the inventory model is also obtained from a 22-sale transaction data chosen for the case study at Minang Mart. In this case, the model is represented as a binary 22x51 matrix or D_{22x51} in which there are 51 goods that are considered in those 22 transactions. Given the minimum support of 13%. Then, solving the model applying apriori algorithm will give the solution of assosiation rules, namely
1.{lifeboy} $\Rightarrow$ {pepsodent} with confidence of 0,6.
2.{pepsodent} $\Rightarrow$ {pepsodent} with confidence of 0,428.

Thefirst rule says that if people buy lifeboy (soap), then they will buy pepsodent (tooth paste) with the confidence of 60 %. Otherwise, the second rule mentions that if people buy pepsodent, they will buy lifeboy with the confidence of 42,8%. This result shows that the lifeboy and tooth paste should be placed closed each other. The purchase of lifeboy will increase the sales of pepsodent with the probability of 60%. Otherwise, the purchase of pepsodent will increase the sales of lifeboy with the probability of 42,8%. So the purchase of lifeboy is better than that of pepsodent in order to boost another item. Hence, lifeboy should be supplied more as a stock than pepsodent.

CONCLUSION

Nowadays, competition in business world, especially in sales industry leads the business people to find out a strategy to increase their sales. Based on the sales transaction data, the transactions can be examined to decide what items typically appear together, e.g., which items customers typically buy together in a database of supermarket transactions. This in turn gives insight into questions such as how to market these products more effectively, how to classify them in store layout or product packages, or which items to offer on sale to boost the sale of other items. There are two methods that can be applied, namely apriori and fp-growth algorithms.

Apriori algorithm is an innovative method to determine association rules on large scale allowing implication outcomes that consist of more than one item. While fp-growth algorithm is an algorithm that allows frequent itemset discovery without candidate itemset generation. The comparison of these two algorithms leads to the same result in which the fp-growth algorithm is better than apriori algorithm. Finding that rules will require to find the confience and the support of all items with all possible combination itemsets. Based on 22 transactional data, the inventory model is represented as a binary matrix D_{22x51} in which there are 51items that are considered in those 22 transactions.

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Given the minimum support of 13%. The solution of the model will lead to the association rules that if people buy lifeboy (soap), then they will buy pepsodent (tooth paste) with the confidence of 60 %. Otherwise, if people buy pepsodent, they will buy lifeboy with the confidence of 42,8%. In this case, , the purchase of lifeboy is better than that of pepsodent in order to increase another item. Moreover, lifeboy should be supplied more as a stock than pepsodent.

REFERENCES

[1] Agrawal,R., Mannila, H., Srikant, R., Toivonen, H., & Verkamo, A. I. (1996). Fast discovery of association rules. In U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, & R. Uthurusamy (Eds.), *Advances in knowledge discovery and data mining* (pp. 307–328). Menlo Park, CA: AVAAI Press.Springer.

[2] A. Nursikuwagus and T. Hartono. (2016). *Implementation of Apriori Algorithm for Analyzing Sales with Web Based*. Journal Simetris.

[3] Dave Witte Morris & Joy Morris. (2016). *Proofs and Concepts the Fundamentals of Abstract Mathematics*. University of Lethbridge.

[4] Frank R.G, William P.F, & Steven B.H. (2010). *A First Course in Mathematical Modeling*. USA: Brooks/Cole.

[5] Hermawati, Fajar Astuti. (2013). *Data Mining*. Yogyakarta : Andi Offset.

[6] Kuo M.H, Kusniruk A.W, Borycki E.M, & Greig D. (2009). *Application of the Apriori Algorithms for Adverse Drug Reaction Detection*. Journal NCBI.

[7] Kusrini dan Luthfi, E.T. (2009). *Mining Data Algorithms*. Yogyakarta: Andi Offset.

[8] L.Hakim & A.Fauzy. (2015). *The Pattern Determination of Traffic Accident Relationship Using Association Rule Methods with Apriori Algorithms*. Research Gate.

[9] L.J.Bain dan M.Engelhardt. (2000). *Introduction to Probability & Mathematical Statistics*. Cengage Learning, Inc. USA: Brooks/Cole.

[10] Pria Nita & RB Fajriya Hakim. (2015). *Application of Association Rule Methods Using Apriori Algorithms to Analyze the Data Pattern of Aircraft Accidents from 1967-2014 in Indonesia*. Proceeding of National Seminar on Mathematics and Educational Mathematics, UMS

[11] Rohayati, Sinambela Sarton. (2008). *The Effect of Promotion Mix on Sales Increase at PT. Aquasolve Sanari*. Ekonomika. Vol IV 1-19.

[12] Salahuddin, Muhammad & Sukamto, Rosa Ariani. (2011). *Software Engineering.* Bandung : Modula.

[13] Christian Bolgelt & Otto von Guericke. 2005. *An Implementation of the FP-Growth Algorithm*. University of Hamburg.

[14] Kumar B.S & Rukmani K.V. 2010. *Implementation of Web Usage Mining Using Apriori and FP-Growth Algorithms*. International Journal of Advanced Networking and Application.

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