

# Application of the Apriori Algorithm in Supporting Sales Strategies at Yolanda Bakery

Adinda Febiola\*, Michael Orlando A. Purba, Fernando Siahaan, Shamil Azam, Putrama Alkhairi, Abdi Rahim Damanik

Information Technology Study Program, Sekolah Tinggi Ilmu Komputer Tunas Bangsa, Pematangsiantar, Indonesia

Jl. Sudirman, Banjar, Kec. Siantar Bar., Kota Pematang Siantar, Sumatera Utara 21142, Indonesia

Email: <sup>1</sup>\*adindafebiola2005@gmail.com, <sup>2</sup>mikaelpurba14@email.com, <sup>3</sup>siahaanfernando18@gmail.com, <sup>4</sup>shamilazam12@gmail.com

Correspondence Author Email: adindafebiola2005@gmail.com

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**Abstract**—Yolanda Bakery is a small-scale bakery business that sells various types of bread, cakes, and other flour-based products, generating daily transaction data that can potentially be used to analyze consumer purchasing patterns. However, this data has not been optimally processed, so sales strategies, display arrangements, and promotional planning still rely on intuition rather than accurate information. To address this issue, this study aims to identify associations between products that are frequently purchased together using the Apriori Algorithm as an analytical approach. The dataset used consists of a collection of daily transactions that then undergo preprocessing and are converted into binary format to suit pattern analysis. The frequent itemset results show that several products, such as Bread (52%), Cakes (28%), and Medialuna (28%), have a relatively high occurrence rate compared to other items. In the association rule formation stage, significant patterns were found, such as Medialuna → Bread and Cake → Bread, with support values of 12% and confidence values of 44%, respectively, indicating a tendency to purchase products together even though the lift value was in the range of 0.85. Heatmap visualization then clarified the relationship between products by displaying combinations of items that appeared more frequently together in transactions. The results of this analysis can be implemented in the form of bundling strategies, display rearrangement, and promotion optimization to increase marketing effectiveness and support more accurate decision-making at Yolanda Bakery.

**Keywords:** Apriori; Product Association; Purchase Patterns; Transaction Data; Sales Strategy

## 1. INTRODUCTION

Yolanda Bakery is one of the bakery businesses operating amid increasing competition in the food industry, especially in bread and cake products, which are now increasingly in demand by various groups of people. As a shop that provides various types of bread, cakes, and other flour products, Yolanda Bakery serves transactions every day, resulting in sales data that continues to grow over time. In a competitive industry, many companies are trying to increase their turnover because there are more and more businesses operating in the same field, including the bakery industry, which generally uses wheat flour as the main raw material in its production process (Alboalebrah, 2025). Bread itself has long been known as a food that has grown rapidly; today, bread is not only a snack but also a staple food for breakfast because of its abundant nutritional content. The bread industry has also become one of the strongest sectors in the food and beverage industry, and it is becoming easier to find as more and more businesses are entering this field (L. Zhang, 2025). The increasing popularity of bread among various segments of society has created greater business opportunities in this sector (Yang, 2025). Therefore, amid increasingly fierce competition, sales activities play an important role in supporting the achievement of company goals and growth (Liu, 2025).

However, despite Yolanda Bakery's high daily transaction volume, the store still faces various obstacles in managing and utilizing its sales data. Sales strategies, stock management, and promotional packages are still done manually based on intuition and experience, often resulting in inaccurate predictions of high-demand products, excess stock, and suboptimal product placement in store displays (Manochitra, 2025). In addition, the growing amount of transaction data has not been fully utilized to identify customer purchasing patterns, such as products that are often purchased together or sales trends at certain times (Xue, 2025). In fact, this information is very important to support more targeted marketing strategies, improve inventory efficiency, and assist in more focused and data-driven decision making (Llanos, 2024). Previous studies have shown that various data analysis methods have been applied in the bakery and pastry industry, but each still has its limitations (J. Zhang, 2025). First, research conducted by Pratama (2024) using K-Means Clustering was able to group products based on sales levels, but could not reveal the relationship between products, making it less than optimal for bundling recommendations (Wang, 2025). Next, research conducted by Lestari and Hidayat (2022) applying the FP-Growth method successfully identified product pairs that are often purchased together, but did not consider time or seasonal factors that greatly affect bread sales (Elquthb, 2025). Finally, research conducted by Wulandari (2022) used Decision Tree C4.5 to predict a decline in demand, but only focused on the prediction aspect without analyzing the overall purchasing pattern (Li, 2024). The limitations of these studies indicate that further research is needed to explore transaction patterns in a more comprehensive, relevant, and operational manner for small-scale bakery businesses such as Yolanda Bakery. Therefore, an analytical approach is needed that not only maps consumer purchasing patterns but also provides a strong foundation for developing more effective and targeted sales strategies (Alrahwan, 2024).

To address the various issues underlying the research, one of the methods used to overcome these issues is the Apriori algorithm. The Apriori algorithm is an analytical approach that can explore patterns of relationships between products in a more in-depth and systematic manner (Gan, 2024). The Apriori Algorithm works by identifying itemsets or

combinations of products that frequently appear together in sales transactions through support and confidence calculations (Yu, 2024). In this way, hidden purchasing patterns can be revealed, such as products that are usually purchased together, demand trends at certain times, and the potential for developing more attractive sales packages (Freyman, 2024). The information generated from Apriori analysis not only helps the store determine bundling and promotion strategies, but also supports more accurate stock management and more effective display arrangements based on consumer behavior patterns (Cao, 2024). This data-driven approach is expected to improve operational efficiency and support more objective decision-making at Yolanda Bakery. In addition to providing a more comprehensive understanding of consumer purchasing patterns, the Apriori Algorithm also has a number of advantages that support its application in the case of Yolanda's Bakery. One of its advantages is its ability to produce association rules that are easy to understand and can be directly applied in an operational context, such as display window arrangements, product bundling, or promotional planning. Apriori also allows researchers and business people to adjust the support and confidence values so that the analysis results can be tailored to the needs and characteristics of the data (Y. Zhang, 2024). In addition, its iterative analysis structure makes this algorithm very effective for small to medium-scale transaction data, making it suitable for use by MSME-scale bakery businesses such as Yolanda Bakery. Apriori's effectiveness in uncovering purchasing patterns is also reinforced by various previous studies. In a study conducted by Budiman (2024), it was shown that Apriori can help local bakeries identify the highest-selling product combinations, thereby significantly improving their display strategies (Lu, 2024). Furthermore, research conducted by Marpaung and Sihotang (2023) on small-scale bakery businesses also found that the use of Apriori was able to increase the accuracy of stock planning by up to 25% thanks to the clear association patterns between one product and another (Brendle, 2024). Finally, Fitriani (2021) emphasized that the results of Apriori analysis are easier to interpret than clustering or classification methods, making it highly relevant for MSME players who need practical, immediately usable information that does not require complex data analysis skills (Deng, 2023). Through this research, it has been proven that Apriori is the right method to help Yolanda Bakery optimize the use of transaction data and support more accurate and evidence-based decision-making.

Based on this description, this study aims to present a more accurate and relevant analytical approach in understanding consumer purchasing patterns at Yolanda Bakery. Through the application of the Apriori Algorithm, this study is expected to be able to explore product association patterns more accurately so that they can be used to design more targeted bundling, promotion, and stock management strategies. In addition to providing a deeper understanding of purchasing trends, the results of this analysis are also expected to support more objective decision making and improve the operational efficiency of the store. Thus, this study not only seeks to overcome the limitations of previous methods, but also makes a real contribution to business development through the optimal and sustainable use of transaction data.

## 2. RESEARCH METHODOLOGY

### 2.1 Research Dataset

Based on the research needs to understand transaction patterns in greater depth, the data used in this study was taken from the Kaggle platform. This dataset contains 50 observations from a bakery and includes four main variables, namely Date, Time, Transaction, and Item. This data structure is then presented as an initial snippet to provide an overview of the form and characteristics of the data to be analyzed using the Apriori Algorithm. The dataset for this study is as follows:

**Table 1.** Research Dataset

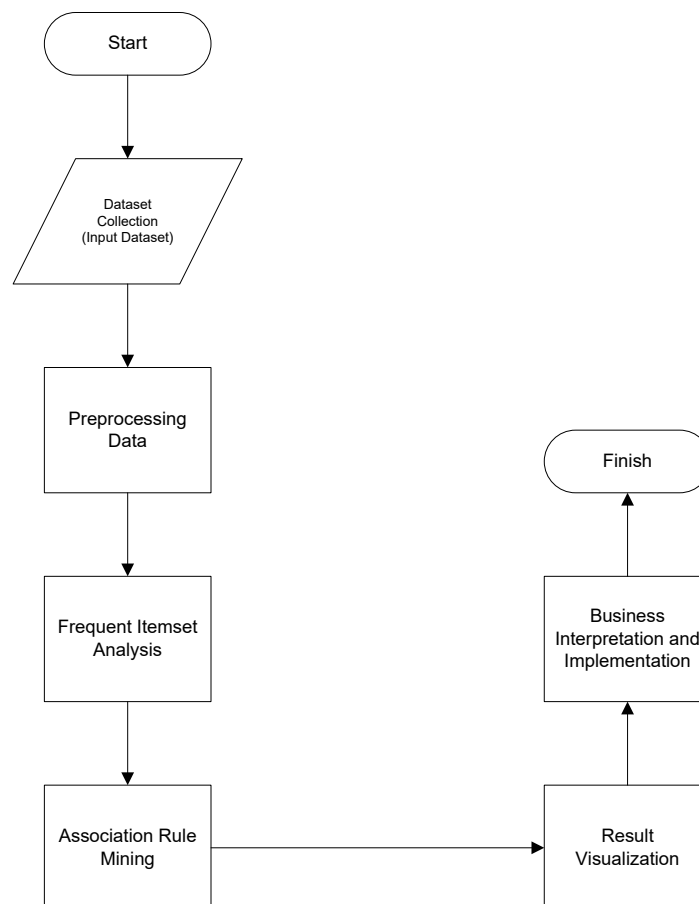
No	Date	Time	Transaction	Item
1	30/10/2016	9:58:11	1	Bread
2	30/10/2016	10:05:34	2	Skandinavia
3	30/10/2016	10:05:34	2	Skandinavia
4	30/10/2016	10:07:57	3	Hot Chocolate
5	30/10/2016	10:07:57	3	Jam
6	30/10/2016	10:07:57	3	Cookies
7	30/10/2016	10:08:41	4	Muffin
8	30/10/2016	10:13:03	5	Coffee
9	30/10/2016	10:13:03	5	Cake
10	30/10/2016	10:13:03	5	Bread
11	30/10/2016	10:16:55	6	Medialuna
12	30/10/2016	10:16:55	6	Cake
13	30/10/2016	10:16:55	6	Muffin
14	30/10/2016	10:19:12	7	Medialuna
15	30/10/2016	10:19:12	7	Cake
...	.....	.....	....	....
50	30/10/2016	10:19:12	7	Tea

Table 1 shows the research dataset, which is sales transaction data recorded on October 30, 2016, at a bakery or café, where each row contains information about the transaction time, transaction number, and items purchased. Each transaction has the same Transaction ID for each item purchased at the same time, so one transaction number can contain

several products at once. For example, in Transaction 3, there are three items purchased at the same time, namely hot chocolate, jam, and cookies. The same pattern can also be seen in other transactions, such as Transaction 5, which contains coffee, cake, and bread, and Transaction 7 with four items at once: medialuna, cake, coffee, and tea.

## 2.2 Research Framework

The research framework is a systematic representation that describes the flow and stages of research, from problem formulation to interpretation of results. The following is our research framework, which is designed to provide a visual guide to the analysis process, from the collection of transaction data to the application of analysis findings to the business strategy of Yolanda Bakery. Our research framework can be seen in Figure 1 as follows:



**Figure 1.** Research Framework

Figure 1 shows the research framework, which describes the complete flow of the analysis process carried out from dataset collection to the interpretation of results. The following are the stages carried out in this study:

a. Start

This stage is the starting point of the data analysis process using the Apriori algorithm. In this section, researchers begin the entire work process, starting from concept preparation, analysis requirements, to initial decisions regarding the parameters to be used in the data mining process.

b. Dataset Collection (Input Dataset)

In the dataset collection stage, transaction data is collected from specific sources, such as a bakery dataset available on the Kaggle platform. The dataset generally contains important information such as transaction date, time, transaction ID, and items purchased by customers. This data is then used as the main input to be processed further in the next stage.

c. Data Preprocessing

The data preprocessing stage is carried out to ensure data quality and consistency before analysis. This process includes cleaning the data of duplicates, handling missing values, aligning data formats, and converting transactions into a format suitable for the Apriori algorithm, such as basket format. Preprocessing is important to avoid analysis errors and produce accurate patterns.

d. Frequent Itemset Analysis

Frequent Itemset Analysis is a process to find combinations of items that most frequently appear together in a transaction. By using a minimum support threshold, the system identifies which itemsets appear frequently enough to

be considered relevant for the association rule formation step. The result of this stage is a list of itemsets that meet the frequency criteria.

e. Association Rule Mining

Once the frequently occurring itemsets have been identified, the next step is to form association rules or “If–Then” patterns. At this stage, the Apriori algorithm generates rules based on support, confidence, and lift values. These rules describe the relationships between products in transactions, such as products that tend to be purchased together.

f. Visualization of Results

Visualization is performed to present association patterns in graphical form, such as support-confidence plots, rule network diagrams, or heatmaps. This visual presentation aims to facilitate the understanding and interpretation of the rules found, making it easier to see the relationships between items intuitively.

g. Business Interpretation and Implementation

At this stage, the results of analysis and visualization are translated into practical recommendations that are useful for the business. Examples include product bundling strategies, product layout arrangements, stock adjustments, or promotions for products that are often purchased together. This stage is key to ensuring that the mining results provide real value for business decision making.

h. Completion

This stage marks the end of the entire analysis process using the Apriori algorithm. All results, interpretations, and recommendations have been obtained and are ready to be used as a reference for decision making or further research development.

### 2.3 Apriori Algorithm

The Apriori algorithm is an algorithm used to find patterns of relationships between items in a transaction data set (Zhao, 2023). The essence of this method is to find combinations of items that frequently appear together using a step-by-step approach, starting from the simplest combinations of items to the more complex ones (Syahrir, 2023). Apriori utilizes the principle that an item combination can only be considered frequent (frequent itemset) if all subsets of that combination also appear frequently (Guo, 2023). This helps reduce the number of combinations that need to be checked, making the process more efficient. In its application, Apriori calculates the support value to determine how often an item or combination of items appears in all transactions. Combinations that meet the minimum support threshold are retained as frequent itemsets (Al-Jumaili, 2023). After that, the algorithm forms association rules by calculating the confidence value, which is a measure of the strength of the relationship between items in a rule (Ding, 2023). Rules with high confidence values indicate that the items tend to be purchased or appear together in transactions (Zhu, 2023). The Apriori algorithm works as follows (Engineering, 2023):

a. Identify all items in the dataset.

Take all items that appear in the transaction data as the basis for forming the first candidate itemset.

b. Form the initial candidate itemset (C1).

Create a list of all single items as candidate 1-itemsets.

c. Calculate the support value for each item.

The support value is calculated to determine how often an item appears in all transactions.

Formula:

$$\text{Support}_A = \frac{\text{Number of transactions containing } A}{\text{Total number of transactions}} \quad (1)$$

d. Determining the first frequent itemset (F1)

Itemsets that have a support value  $\geq$  minimum support are retained as the first frequent itemset.

Forming the next level of item combination candidates (Ck)

The previous level of frequent itemsets are combined to produce new combinations, for example, from 1 item to 2 items, from 2 items to 3 items, and so on.

e. Performing the pruning process

Candidate item combinations that have infrequent subsets are discarded.

Apriori principle:

If an itemset is infrequent, then all larger itemsets containing that itemset are also infrequent.

f. Calculating the support value for Ck

The support value of each candidate combination is recalculated using the same formula.

g. Determine advanced frequent itemsets (Fk)

Only candidates that meet the minimum support are stored as frequent itemsets. Form association rules from frequent itemsets. Frequent itemsets are broken down into antecedents (A) and consequents (B) to form the rule  $A \rightarrow B$ .

h. Calculate the confidence value

Confidence indicates how strong the relationship  $A \rightarrow B$ .

Formula:

$$\text{Confidence}_{A \Rightarrow B} = \frac{\text{Support}(A \cap B)}{\text{Support}(A)} \quad (2)$$

i. Selecting valid rules

Association rules are selected if they meet the specified minimum confidence.

### 3. RESULT AND DISCUSSION

#### 3.1 PreProcessing Data

Before performing the analysis process using the Apriori method, the first step is to compile the transaction data into a binary table. In this table, each row represents a transaction, while each column indicates the presence of an item in that transaction. A value of 1 indicates that the item was purchased in the relevant transaction, while a value of 0 indicates that the item did not appear in the transaction. Presenting the data in binary form is important as a basis for calculating support and forming frequent itemsets in the next stage. The transaction data used in this study is presented as follows:

**Table 2.** Binarization Transaction Table

Transaction	Bread	Skandinavia	Hot Chocolate	Jam	Cookies	Muffin	Coffee	Cake	Medialuna
1	1	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0
3	0	0	1	1	1	0	0	0	0
4	0	0	0	0	0	1	0	0	0
5	1	0	0	0	0	0	1	1	0
6	0	0	0	0	0	1	0	1	1
7	0	0	0	0	0	0	1	1	0
8	1	0	0	0	0	0	0	1	0
9	1	0	0	0	0	1	0	0	0
10	0	1	0	0	0	0	0	0	1

Transaksi	Tea	Mineral Water	Tartine	Farm House	Keranjang
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	0	0	0	0	0
7	1	0	0	0	0
8	0	0	0	0	0
9	0	0	0	0	0
10	0	0	0	0	0

Table 2 shows a binary dataset in the form of a collection of transactions that record what items were purchased by customers. Each transaction is displayed in binary form, where 1 indicates that the item was purchased, and 0 indicates that the item was not purchased. The items recorded include various products such as bread, drinks, cakes, and other bakery products. This data shows that each transaction has a different combination of purchases; some customers only buy one item, while others buy several items at once. This data structure makes it easier to identify consumer purchasing patterns in the next stage of analysis.

#### 3.2 Frequent Itemset

After all transactions are processed using the Apriori method, the next step is to identify frequent itemsets, which are sets of items that appear most frequently in the dataset based on the calculated support values. Itemsets with support values above the minimum threshold are considered significant and are used as the basis for forming association rules. The results of the support calculations for items in the transaction data can be seen in the following table:

**Table 3.** Frequently Occurring Itemsets in Transactions

Frequent Itemsets	Support
{'Bread'}	52%
{'Medialuna'}	28%
{'Coffee'}	2%
{'Cake'}	28%
{'Skandinavia'}	16%
{'Bread', 'Medialuna'}	12%
{'Bread', 'Cake'}	12%
{'Medialuna', 'Cake'}	12%

Table 3 Transaction Items shows the results of support calculations for each item and combination of items that are considered to appear frequently in transactions. The support value describes the percentage of transactions that contain

a particular item or pair of items. For example, Bread has a support of 52%, which means that more than half of transactions involve the purchase of bread. Items such as Cake and Medialuna also appear quite frequently, with a support of 28% each. Meanwhile, Coffee only has a support of 2%, indicating that this item is rarely purchased. In addition to single items, this data also displays frequent itemsets in the form of combinations of two items, such as {'Bread', 'Medialuna'}, {'Bread', 'Cake'}, and {'Medialuna', 'Cake'}, each of which has a support of 12%. This means that these item combinations appear together in 12% of all transactions. This information is important for understanding consumer purchasing patterns and forms the basis for establishing association rules in the next stage.

### 3.3 Association Rule

After frequent itemsets have been successfully identified, the next step is to form association rules to see the relationships between items that appear together in transactions. These association rules are compiled using three main measures, namely support, confidence, and lift, which help assess the strength and relevance of the relationship between the antecedent (trigger item) and the consequent (following item). The results of the association rule calculations from the dataset are shown in the following table:

**Table 4.** Transaction Item Association Rules Table

Antecedent	Consequent	Support	Confidence	Lift
{'Medialuna'}	{'Bread'}	12%	44%	85%
{'Cake'}	{'Bread'}	12%	44%	85%
{'Bread'}	{'Medialuna'}	12%	23%	85%
{'Bread'}	{'Cake'}	12%	23%	85%

The association rules show that when consumers buy Medialuna, they tend to also buy Bread, with a support value of 12%, confidence of 44%, and lift of 0.85. In addition, the purchase of Cake also tends to be followed by the purchase of Bread, as indicated by a support value of 12%, confidence of 44%, and lift of 0.85. Meanwhile, when consumers buy Bread, there is a possibility that they will also buy Medialuna, although the relationship is weaker, as seen from the confidence value of 23% and lift of 0.85. The same pattern appears in the Bread → Cake rule, where confidence of 23% and lift of 0.85 indicate that the relationship between the two is not very strong, but still occurs in some transactions.

### 3.4 Visualization of Purchasing Patterns

After conducting an initial analysis to understand the basic characteristics of the dataset, the next step is to explore the relationships between variables in greater depth. At this stage, a heatmap is used as a visualization tool that can comprehensively display correlation patterns. Through the heatmap, the interrelationships between variables can be observed more clearly, making it easier for researchers to identify patterns, trends, and interactions that may influence the results of further analysis. The following is an image of a heatmap of itemsets that frequently appear together in transactions:



**Figure 1.** Heatmap of Correlation Between Items in Transactions

Figure 1 Heatmap shows the correlation between items based on how often they are purchased together in a single transaction. A value of 1.00 on the diagonal indicates the relationship between each item and itself, so the value is always maximal. Meanwhile, values outside the diagonal indicate the strength of the relationship between two items; the higher the value, the more often the two items are purchased together. From this visualization, it can be seen that Bread, Medialuna, and Cake have relatively similar relationships with a value of 0.12, indicating that the three are quite often purchased together, while Coffee has a lower value compared to other items, indicating that coffee appears less frequently in purchase combinations. The color variation from light blue to dark blue helps to show which relationships are strong and which are weak, so that overall, this heat map provides a clear picture of consumer purchasing patterns at the bakery.

### 3.5 Business Interpretation and Implementation

The results of the analysis obtained in this study indicate that consumer purchasing patterns at bakeries form a combination of items that appear consistently, particularly the relationship between Medialuna, Bread, and Cakes, which have quite prominent support and confidence values. This association pattern indicates customer preferences for certain product groups that tend to be purchased together, which can be used as a basis for formulating more targeted business decisions. Relevant strategic implementations include developing product bundling packages, optimizing display optimization by placing frequently associated items in close proximity, and formulating promotional strategies that focus on product pairs with high lift values to encourage increased sales conversions. Thus, the results of the Apriori analysis not only provide a deep understanding of consumer shopping behavior patterns, but also provide a strong basis for improving the effectiveness of marketing strategies and store operational efficiency.

## 4. CONCLUSION

The results of the Apriori algorithm analysis on Yolanda Bakery transaction data show that consumer purchasing patterns tend to form consistent links between certain products, especially Medialuna, Bread, and Cakes. These three products not only have relatively high support values, but also generate association rules with confidence that indicates a real tendency for consumers to purchase items together. These empirical findings identify customer preferences for product combinations based on similarity in taste, category, or consumption function. In addition, lift values close to one indicate that the relationship between products is moderate, so that purchasing patterns do not occur entirely by chance, but also do not show very strong dependencies. Nevertheless, these patterns still provide important insights for stores in formulating more effective sales strategies. From a business implementation perspective, these association results can be used to improve the effectiveness of product layout, for example by placing Medialuna, Bread, and Cakes in adjacent display areas to make it easier for customers to see them as related combinations. In addition, bundling and cross-selling strategies can be designed by utilizing product pairs that have the highest support and confidence to encourage an increase in average transaction value. Thus, this analysis not only provides an understanding of customer shopping behavior, but also provides a strategic foundation for data-driven decision making in improving the competitiveness and operational effectiveness of stores.

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