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Application of Apriori Algorithm to Find Flower Purchase Patterns

Daffa Yauzan Tusianto[1], Ahmad Fairuzabadi[2*], Sujito[3]
[1] Department of Informatics Engineering, University of Widyagama Malang, Jl. Borobudur No. 35 Malang, Indonesia
[2] Department of Digital Business, University of Widyagama Malang, Jl. Borobudur No. 35 Malang, Indonesia
[3] Department of Information Technology, STMIK PPKIA Pradnya Paramita Malang, Jl. LA Sucipto No 249A Malang, Indonesia

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ABSTRACT

This research aims to apply the Apriori algorithm in analyzing flower purchase patterns at a flower shop. Apriori algorithm is used to identify product combinations that are often purchased together, in the hope of finding purchasing patterns that can be utilized to improve marketing strategies and store operational efficiency. Transaction data from the shop is processed to extract frequent itemsets and generate association rules by setting the right threshold of support and confidence values. The results of this study show that flower combinations such as Tulip and Bougenville frequently co-occur in purchases, with significant support-confidence products. These findings provide insights into consumer purchasing behavior that can be used to recommend product bundling or product rearrangement in stores. This research contributes to the application of data mining in the retail sector, particularly in increasing sales and customer satisfaction in flower shops.

Corresponding Author:

Ahmad Fairuzabadi
Department of Business Digital
Faculty of Science and Information Technology, University of Widyagama Malang
Jl. Borobudur No. 35 Malang, Jawa Timur
Email: fairuz@widyagama.ac.id

INTRODUCTION

Trading activities in the business world always have a dynamic and competitive pattern, so business people need to find effective strategies to increase sales and market their products. Every industry generates purchase transaction data from each consumer as a result of the buying and selling activities that take place [1].

In digital era, data analysis has become very important for businesses to understand consumer behavior and improve marketing strategies. One method that is widely used in data analysis is the Apriori algorithm, which is part of the association rule mining technique. Association rule mining is a data mining method used to identify relationships or associations between various combinations of items in a dataset [2]. This algorithm allows extracting purchase patterns from large transaction data, thus providing valuable insights into consumer habits.

Consumer purchasing patterns can provide strategic information for business owners, especially in determining the stock of goods and designing more effective promotions. For example, research shows that by applying the Apriori algorithm, stores can identify combinations of products that are often purchased together, which can help in product layout and inventory management [3] [4] [5].

The Apriori algorithm is an algorithm that can be used to apply market basket analysis to find association rules that meet support and confidence limits [6]. This apriori algorithm will be suitable to be applied when there are several item relationships to be analyzed [7].

The Apriori algorithm has been applied in various sectors, including retail, food and beverage, and health products. In the context of flower sales, the application of this algorithm can help flower shop owners to understand what types of flowers are often bought together by customers. For example, research in optical stores shows that the application of this algorithm can generate association rules that help in the arrangement of product packages [8].

Some previous studies have shown the successful use of the Apriori algorithm in finding purchasing patterns. Among them is research conducted at UD. Borimin who found a combination of rice brands using this algorithm with significant results [9]. In addition, the use of the Apriori algorithm at Queen Parfum succeeded in identifying combinations of perfumes that are often purchased together, such as Taylor Swift perfume which is often purchased with Bacarat perfume [10].

With increasing competition in the flower market, the application of the Apriori algorithm to discover flower purchase patterns is becoming increasingly relevant. This will not only help in improving operational efficiency but also increase customer satisfaction through more targeted offers.

Through the application of the Apriori algorithm, flower shop owners can optimize their marketing strategies by understanding consumer buying patterns. This research aims to further explore how this algorithm can be applied specifically in the context of flower sales, as well as provide data-driven recommendations for better business decision-making.

References from various studies show that the application of the Apriori algorithm has great potential in increasing understanding of consumer behavior and improving business strategies [11] [12]. Thus, this research is expected to make a significant contribution to the flower selling industry.

METHOD

Customer buying patterns at flower shops are often influenced by various factors, such as individual preferences, specific event needs, or seasonal trends. Identifying these patterns can not only provide deeper insights into consumer behavior but also be the basis for more targeted strategic decision-making.

In this context, the Apriori algorithm was chosen as an analysis tool due to its ability to uncover hidden relationships among items in transaction data. This method has been widely used in various sectors, from retail to services, as a reliable approach in discovering purchasing patterns and relationships between products.

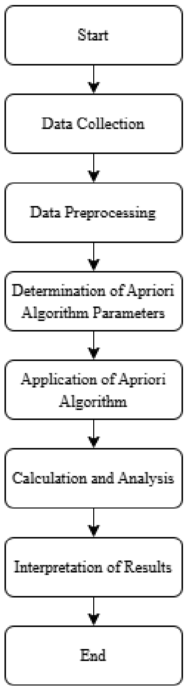

Figure 1. Research Methodology

This research was conducted through several systematic stages to ensure valid and relevant analysis. The following are the stages that were carried out:

- Data Collection: Collecting flower sales transaction data from flower shops during a certain period.
- Data Preprocessing: Converts the transaction data into a binary format, where each item is assigned a value of '1' if present in the transaction or '0' if not.
- Apriori Algorithm Parameter Determination: Setting a minimum support value of 30% to determine frequent itemsets and setting a minimum confidence value of 70% to generate relevant and strong association rules.
- Application of Apriori Algorithm: Using the Apriori algorithm to find frequent itemsets based on the minimum support value set.

Calculation and Analysis: Filtering rules with confidence values above 70% to ensure relevance and analyzing the most significant item combinations.

Interpretation of Results: Develop recommendations based on the findings, such as product bundling strategies or rearrangement of product layouts in stores.

2.1. Flower Sales Transaction Data

The dataset used in this study is a flower sales transaction data from a flower shop over a 1-month period. Each transaction records the types of flowers purchased by customers, providing an insight into consumer preferences and potential relationships between different types of flowers.

By studying this data, we can understand how certain flowers are often purchased together in a single transaction, which then becomes the basis for building association rules. The following is the transaction table of the flower sales transaction data that will be analyzed further :

Table 1. Flower Sales Transaction Data

No	Purchased Items
1	Asoka, Mawar, Kamboja, Bougenville, Anggrek
2	Bougenville, Anggrek, Kamboja, Kemuning
3	Anggrek, Bougenville, Melati, Kamboja, Tulip
4	Bougenville, Kemuning, Tulip, Asoka
5	Bougenville, Mawar, Tulip, Asoka, Kamboja
6	Melati, Kamboja, Anggrek, Asoka
7	Anggrek, Bougenville, Kemuning, Tulip
8	Bougenville, Mawar, Kemuning, Asoka, Tulip
9	Asoka, Tulip, Kemuning, Mawar
10	Tulip, Melati, Kemuning, Kamboja
11	Melati, Kemuning, Bougenville, Asoka
12	Kamboja, Asoka, Bougenville, Anggrek
13	Tulip, Bougenville, Anggrek
14	Bougenville, Tulip, Mawar
15	Anggrek, Asoka, Bougenville, Tulip
16	Kemuning, Mawar, Bougenville, Anggrek
17	Anggrek, Kamboja, Melati, Tulip
18	Mawar, Bougenville, Tulip, Kamboja, Anggrek
19	Kamboja, Melati, Mawar
20	Asoka, Kemuning, Tulip, Bougenville, Kamboja
21	Anggrek, Asoka, Melati, Bougenville
22	Asoka, Bougenville, Kamboja, Anggrek, Kemuning
23	Tulip, Mawar, Kamboja, Bougenville
24	Tulip, Asoka, Melati
25	Bougenville, Mawar, Tulip, Melati
26	Kamboja, Kemuning, Anggrek, Mawar
27	Kamboja, Asoka, Tulip
28	Melati, Mawar, Asoka, Kemuning
29	Melati, Anggrek, Mawar, Kamboja
30	Melati, Mawar, Bougenville, Asoka, Kemuning

2.2. Tabulation of Transaction Data

After understanding the structure and general characteristics of flower sales transaction data, the next step is to present the data in a more organized form to facilitate further analysis. The data tabulation process aims to organize the information systematically so that purchasing patterns can be identified more clearly. In this context, each transaction will be represented as a combination of items that indicate the flowers purchased by the customer.

Data tabulation also allows us to recognize the frequency of occurrence of each type of flower as well as the combination of flowers that often appear together in a single transaction. Thus, this data becomes a solid foundation for the application of the Apriori algorithm in identifying purchase patterns. The following is a tabulation of flower sales transaction data used in this study :

Table 2. Tabulation of Transaction Data

No	Mawar	Melati	Kamboja	Anggrek	Bougenville	Tulip	Asoka	Kemuning
1	1	0	1	1	1	0	1	0
2	0	0	1	1	1	0	0	1
3	0	1	1	1	1	1	0	0
4	0	0	0	0	1	1	1	1
5	1	0	1	0	1	1	1	0
6	0	1	1	1	0	0	1	0
7	0	0	0	1	1	1	0	1
8	1	0	0	0	1	1	1	1
9	1	0	0	0	0	1	1	1
10	0	1	1	0	0	1	0	1
11	0	1	0	0	1	0	1	1
12	0	0	1	1	1	0	1	0
13	0	0	0	1	1	1	0	0
14	1	0	0	0	1	1	0	0
15	0	0	0	1	1	1	1	0
16	1	0	0	1	1	0	0	1
17	0	1	1	1	0	1	0	0
18	1	0	1	1	1	1	0	0
19	1	1	1	0	0	0	0	0
20	0	0	1	0	1	1	1	1
21	0	1	0	1	1	0	1	0
22	0	0	1	1	1	0	1	1
23	1	0	1	0	1	1	0	0
24	0	1	0	0	0	1	1	0
25	1	1	0	0	1	1	0	0
26	1	0	1	1	0	0	0	1
27	0	0	1	0	0	1	1	0
28	1	1	0	0	0	0	1	1
29	1	1	1	1	0	0	0	0
30	1	1	0	0	1	0	1	1
Total	14	12	16	15	20	17	16	13

2.3. 2-Itemset Combination

After tabulating the transaction data, the next step is to identify combinations of two items that frequently appear together in a single transaction. These combinations are the initial focus of the analysis as they can provide insights into direct relationships between products. Identifying 2-itemsets not only helps understand basic buying patterns, but also lays the foundation for more complex analysis on larger combinations of items. Determining the support value of 2-itemset can be obtained using the following formula [13] [14] :

$$support\ (A, B) = \frac{Total\ Transactions\ Covering\ A\ \&\ B}{Total\ Transaction}\ x100\% \quad (1)$$

In the context of flower sales, combinations of two types of flowers that are frequently purchased together may reflect customers' preferences in flower arrangements or specific decoration needs. For this analysis, the minimum support value is set at 30%, so only combinations that meet this threshold will be considered. This approach ensures that the results are practically relevant and reflect significant buying patterns. The following table shows the combinations of two items (2-itemset) that frequently co-occur in transactions :

Table 3. 2-itemset combination

Item A	Item B	Support
Anggrek	Bougenville	37%
Bougenville	Kamboja	30%
Bougenville	Mawar	30%
Asoka	Bougenville	37%
Anggrek	Kamboja	33%
Bougenville	Kemuning	30%
Bougenville	Tulip	40%

2.4. 3-Itemset Combination

After analyzing 2-itemset combinations, the next step is to identify 3-itemset combinations to explore more complex relationships between products. These three-itemset combinations are expected to provide additional insights into more specific customer preferences, such as flowers that are often purchased together for specific needs. Determining the support value of 3 items can be obtained using the following formula [15] :

$$support\ (A, B\ and\ C) = \frac{Total\ Transactions\ Covering\ A,B\ and\ C}{Total\ Transaction}\ x100\% \quad (2)$$

However, based on the analysis results with a minimum support value of 30% using python code, no combination of three items was found that met this threshold. This suggests that the purchase relationship at the three-item level is less significant than the two-item combination. Nonetheless, this finding is still important as it provides insight that customers tend to choose simpler combinations or focus on specific flower pairs. This analysis provides a basis to focus on two-item combinations as a more effective marketing strategy.

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Support and Confidence for 3-itemset:
Empty DataFrame
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2.5. Calculating Confidence Value

Calculating the confidence value on the combination of itemsets can be obtained using the following formula [15]:

$$confidence = P(B \mid A) = \frac{Total\ Transactions\ Covering\ A\ and\ B}{Total\ Transaction}\ x100\% \quad (3)$$

After identifying the combination of items that meet the minimum support value, the next step is to calculate the confidence value for each association rule generated. Confidence describes how strong the relationship is between items in a combination, by indicating the probability of the second item (consequent) occurring when the first item (antecedent) is already present in the transaction.

The calculation of the confidence value is very important as it helps in evaluating the relevance and strength of the association rules found. With a high confidence value, the rule can be considered more reliable and has greater potential to be applied in business strategies, such as cross-promotion or product placement. The following table shows the confidence value calculation for association rules generated from combinations of items that meet the minimum support value :

Table 4. Confidence Value

Item A	Item B	Confidence A to B	Confidence B to A
Anggrek	Bougenville	73%	55%
Bougenville	Kamboja	45%	56%
Bougenville	Mawar	45%	64%

Item A	Item B	Confidence A to B	Confidence B to A
Asoka	Bougenville	69%	55%
Anggrek	Kamboja	67%	63%
Bougenville	Kemuning	45%	69%
Bougenville	Tulip	60%	71%

2.6. Association Rule Formation

After calculating the confidence value for each association rule, the next step is to filter out rules with a confidence value of more than 70%. This value indicates that the relationship between the items in the rule has a high probability, making the rule more reliable and relevant to implement.

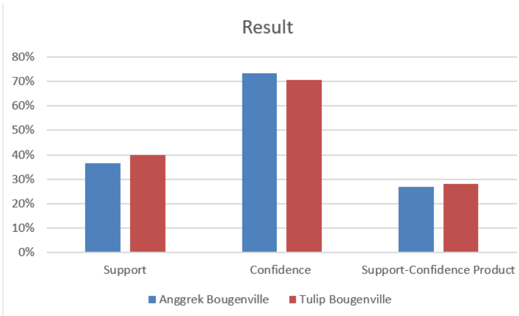
Association rules with confidence values above 70% reflect strong buying patterns, where the presence of one item is highly likely to be followed by another. This finding provides a solid foundation for designing more focused marketing strategies, such as related product promotions or targeted bundling. The following are the association rules with a confidence value of more than 70% generated from the analysis :

Table 5. Association Rule Formation Result

Item A	Item B	Support	Confidence	Support-Confidence
Anggrek	Bougenville	37%	73%	0,2689
Tulip	Bougenville	40%	71%	0,2824

RESULTS AND DISCUSSION

In this study, we examine customer purchase patterns for certain combinations of flower types, namely Anggrek with Bougenville and Tulip with Bougenville. We utilize support, confidence, and support-confidence metrics to evaluate the strength and relevance of the association rules present in our dataset. This analysis aims to determine how often and how reliably these flower combinations are purchased together by consumers.



We can see the comparison between the two flower combinations Anggrek-Bougenville and Tulip-Bougenville based on three metrics: support, confidence, and support-confidence product in the figure above.

The combination of Anggrek and Bougenville appears in 37% of all transactions we analyzed, indicating that more than a third of purchases involve these two flowers. This suggests that customers have a significant preference for this combination, which can be very useful in planning marketing and promotional strategies. The confidence level recorded is 73%, indicating that the presence of Orchids in a transaction has a high probability of being followed by a Bougenville purchase. This reflects the strong correlation between the two flower types in consumer shopping habits.

Moving on to the support-confidence metric, the resulting value is 0.2689. This value provides additional insight into how effective this rule is in describing the frequency as well as the reliability of this combination in prediction. By combining information from support and confidence, we can more accurately gauge how valuable these association rules are in a real context, offering us data that can be used to optimize marketing initiatives.

Meanwhile, the combination of Tulip and Bougenville shows a slightly higher support of 40%. This shows that this combination is even more popular than Orchid and Bougenville, occurring in almost every two out of five transactions. Although the confidence level is slightly lower than the previous combination, at 71%, it is still high enough to show that the presence of Tulip tends to be accompanied by Bougenville in the same transaction. This confirms that these two types of flowers also have a close relationship in the eyes of consumers.

The higher support-confidence value of 0.2824 for the combination of Tulip and Bougenville indicates the greater effectiveness of this rule in the dataset. It not only measures the frequency of occurrence of this combination but also its reliability in predicting co-occurrence, which is crucial for marketing strategies aimed at increasing cross-selling and maximizing customer satisfaction.

The results of this analysis provide valuable insights into consumer buying patterns that can be used by florists in designing more attractive and effective promotions. Identifying product combinations that are often purchased together helps in optimizing product offerings and layouts, which in turn can increase sales and customer satisfaction. With data-driven strategies, businesses can more easily adapt their offerings to changing consumer preferences.

CONCLUSION

Analysis of customer transaction data for Anggrek with Bougenville and Tulip with Bougenville flower combinations revealed consistent purchase patterns and strong consumer preferences. The combination of Tulip and Bougenville showed higher support, while Orchid and Bougenville showed higher confidence. The results of the support-confidence product indicate that both combinations have good potential for marketing and promotion strategies. By understanding these buying patterns, florists and retailers can design more attractive promotions, optimize product arrangement, and increase sales and customer satisfaction. The analyzed data provides valuable insights for adapting strategies based on dynamic customer preferences and improving cross-selling effectiveness.

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