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Association Rule Mining of Consumer Behavior at MOY Supermarket Using Apriori Algorithm

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***Abstract*— MOY Frozen Food is a retail business located in Kediri Regency, specializing in selling frozen food, beverages, and necessities. In recent years, the retail industry has faced numerous challenges, including shifts in consumer behavior, technological advancements, and increasing competition. This study addresses the issue of identifying which products are frequently purchased together and determining appropriate recommendations for consumers. To achieve this goal, association rules are employed to discover correlations and co-occurrences among data sets, which facilitate identifying product relationships within a single transaction. Using the Apriori algorithm with a minimum support threshold of 0.01 and a confidence level of 0.5, implemented in Python, this research successfully generates association rules. The insights derived from these association rules can be leveraged to develop various sales strategies, ultimately enhancing product sales at MOY Frozen Food.**

Index Terms*— association rule mining; apriori algorithm; consumer behavior; product recommendation; sales strategy.

I. INTRODUCTION

Making quick and accurate decisions to determine business strategies is one of the many influential factors that business owners, including those at MOY Supermarket, must consider. The growth and competition in global trade, driven by free-market economies and advances in information technology, have intensified the level of competition, making it more transparent and challenging for companies to meet increasing customer demands [1]. These factors highlight the importance of making business decisions based on data [2], rather than relying solely on intuition. The data used should be derived from the collection of every transaction that occurs.

There are many ways to understand market conditions in the retail business, one of which is by analyzing sales transaction data. Daily, weekly, monthly, or yearly, vast transaction data are stored in the company's database [3]. In the digital era, competition in the retail business is becoming increasingly intense, necessitating new marketing strategies to attract consumers [4]. Digital marketing significantly influences the growth of retail businesses, requiring companies or retail stores to keep up with technological advancements in business, which are key to achieving success [5]. Consequently, the amount of data stored in digital product sales databases will continue to grow, becoming big data, which forms the foundation for the emergence of data mining.

Data mining in economics, particularly in retail business, can help solve business problems, such as identifying patterns in customer transaction behavior. By understanding these patterns, a retail business can more easily make decisions regarding marketing strategies aimed at consumers. One customer behavior that can be identified and analyzed is the combination of products frequently purchased together. Data mining techniques can be used to discover association rules, specifically the association rules between combinations of items, to determine which products are bought simultaneously. This association process utilizes the Apriori algorithm. The Apriori algorithm, which was introduced by Agrawal and Srikant in 1994 [6], is used to determine frequent item sets for Boolean association rules [7].

In a previous study [8] titled " Penerapan Algoritma Apriori Terhadap Data Mining Penjualan di Alfamart Berastagi" 75 association rules were generated with a minimum support of 50% and a confidence of 0.9. Meanwhile, another study [3] titled "Penerapan Data Mining Menggunakan Algoritma Apriori Terhadap Data Transaksi Penjualan Bisnis Ritel" produced 3 association rules with a minimum support of 0.6 and a confidence of 0.8. Both studies focused on retail companies; study [8] utilized RapidMiner software, while study [3] was tested using the Orange tool. In contrast, the current research focuses on a mediumscale retail business and uses Python software for testing.

Business activities in Indonesia are largely conducted by the community through Micro, Small, and Medium Enterprises (MSMEs) [9]. MSMEs also play a crucial role in Indonesia's economy [10], necessitating efforts to enhance their strategies to stay competitive with larger businesses. MOY Frozen Food Supermarket is one such MSME operating in the retail sector, primarily focusing on food products, particularly frozen foods, beverages, and daily necessities. This supermarket must meet the needs of its customers daily and be driven to develop the right sales strategies. To achieve this, the company needs sufficient information for further analysis. For example, data from recorded sales transactions can be used to understand consumer habits or behavior and develop strategies to achieve the desired business goals.

II. Methodology

This study employs the association rule-mining method to analyze consumer purchasing patterns at MOY Frozen Food Supermarket. By uncovering hidden patterns and correlations within sales transaction data, this method allows for a deeper understanding of consumer behavior, which can be leveraged to enhance marketing strategies and inventory management. The Apriori algorithm, a well-known technique in data mining, is utilized in this research due to its efficiency in discovering frequent item sets and generating association rules from large datasets. The process begins with data collection, followed by data pre-processing and mining, where meaningful patterns are extracted. The flowchart illustrating the entire research methodology, including each step of the data analysis and implementation, is presented in **Figure 1.** This structured approach aims to provide actionable insights that can help MOY Frozen Food Supermarket optimize its operations and improve customer satisfaction.

The flowchart in **Figure 1** illustrates the process of applying the Apriori algorithm to analyze consumer purchasing patterns at MOY Frozen Food Supermarket. The process begins with the Data Collection stage, where all relevant sales transaction data is gathered. Following this, a Literature Review is conducted to understand previous studies and establish a theoretical foundation for the research. The next phase involves the Implementation of the Apriori Algorithm, which is divided into two key steps: Data Pre-processing and Data Mining. During data pre-processing, the collected data is cleaned and prepared for analysis to ensure accuracy and consistency. In the data mining step, the Apriori algorithm is applied to identify frequent item sets and extract meaningful association rules. The results of this analysis are then summarized in the Conclusion and Recommendations stage, providing insights and strategic suggestions for the supermarket. Finally, the process ends at the Completion stage, where the research findings are documented and reviewed.

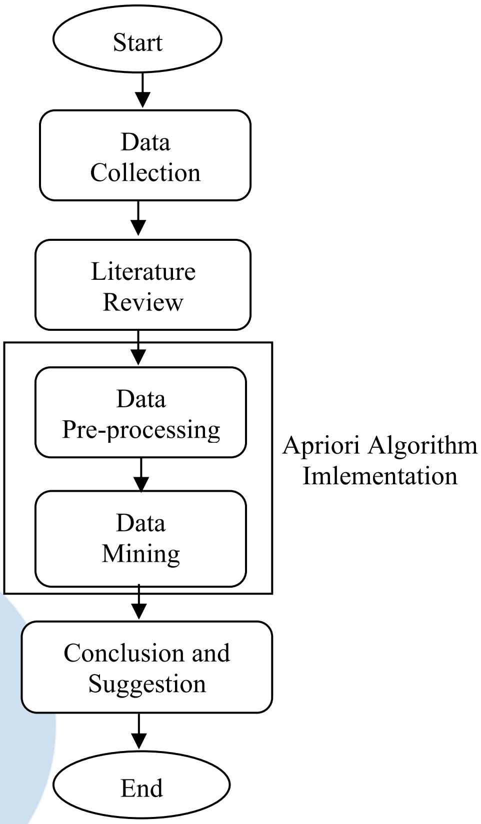

Figure 1. Research Flow

A. *Data Collection*

The data for this study was obtained from the transaction records of MOY Frozen Food Supermarket, located in Kediri Regency, East Java, covering the period from March 1, 2024, to March 13, 2024. A total of 2,544 rows of data were processed, encompassing several key variables: transaction number, transaction date, transaction day, transaction time, customer type, item code, item name, item quantity, and item category. This comprehensive dataset provides a detailed overview of consumer purchasing activities within the specified timeframe, offering a rich source of information to identify purchasing patterns and trends that can inform business strategy and decision-making at the supermarket.

B. *Literature Review*

At this stage, relevant literature sources are sought and gathered, including articles, journals, books, and other references related to the research, particularly those focusing on association methods using the Apriori algorithm. This comprehensive literature review helps to establish a solid theoretical foundation for the study, ensuring that the research is grounded in existing knowledge and methodologies. By examining previous studies and findings, the research can identify gaps in the current literature and better position its contribution to the field of consumer behavior analysis using data mining techniques.

C. Implementasi Algoritma Apriori

The implementation of the Apriori algorithm is carried out using Python tools. The data processing stage is divided into two main phases: data pre-processing and data mining. Data pre-processing is a critical step in data mining analysis, aimed at cleaning [11], reformatting, and preparing the data for analysis, making it easier to handle and more accurate for subsequent steps. This stage involves removing any inconsistencies, errors, or irrelevant information to ensure that the dataset is of high quality and suitable for mining. On the other hand, data mining focuses on extracting previously unknown patterns or useful information from large datasets, transforming them into understandable and actionable insights that can be used to make crucial business decisions [11]. In the context of implementing the Apriori algorithm, several key terms are frequently used, including:

1. *Support*

Support represents the percentage of a particular item combination within a database [12]. The support value of an item is calculated using the following formula [13]:

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

Similarly, the support value of 'n' items is determined using [13]:

$$Support(A \cup B) = \frac{Number\ of\ transactions\ containing\ both\ A\ and\ B}{Total\ number\ of\ transactions} \quad (2)$$

2. *Minimum support*

Minimum support is a process used to find all association rules that meet a specified minimum threshold for support [14]. It is expressed as a percentage or proportion of the total number of transactions. If an item set has a support value (frequency of occurrence) equal to or greater than the minimum support threshold, it is considered a frequent item sets. Minimum support helps filter out infrequent item sets, ensuring the algorithm only processes significant and relevant item sets.

3. *Support count*

Support count refers to the number of times a group of products appears together in the transaction data of a shopping cart [15]. It is a fundamental metric in the Apriori algorithm for determining how often a particular combination of items occurs together across all transactions. For example, if the item sets {Bread, Milk} appears in three out of five transactions, its support count is 3. The support count calculates the support value, which then helps identify frequent item sets that meet a certain threshold.

4. *Confidence*

Confidence measures the certainty or strength of the relationship between items in the Apriori algorithm [16]. A high confidence value indicates that item B is also likely to appear when item A appears, thereby validating the reliability of the association rule. Mathematically, confidence is defined as the ratio of the number of transactions that contain both the antecedent and the consequent to the number of transactions that contain only the antecedent. The formula for confidence is given by equation 3 [17].

$$Confidence(A \rightarrow B) = \frac{Support(A \cup B)}{Support(A)} \quad (3)$$

Where:

A is the antecedent (the item or set of items on the left-hand side of the rule).

B is the consequent (the item or set of items on the right-hand side of the rule).

5. *Minimum confidence*

The minimum confidence is the value that meets the minimum requirement for confidence [18]. This value measures how often item Y appears in transactions that contain item X. If the confidence of the rule X → Y is greater than or equal to the specified minimum confidence, then the rule is considered strong and significant. For example, if the minimum confidence is set at 70%, the rule X → Y will only be considered if at least 70% of the transactions containing X also contain Y.

6. *Itemsets*

An item sets is a set of items contained within a set processed by the system [17]. In the context of data mining and association analysis, item sets are used to discover patterns or relationships between items that frequently appear together in transaction datasets. An item sets can consist of a single item or a combination of multiple items.

7. *Frequent item set*

A frequent item set is a collection of items that meet a minimum support threshold. In the context of the Apriori algorithm, frequent item sets are used to identify patterns or relationships between items that frequently appear together in transactions. For example, if {Bread, Milk} often appears together in many transactions, {Bread, Milk} is considered a frequent item set. The discovery of frequent item sets is useful in various applications such as product recommendation, shopping basket analysis, and product placement optimization in retail stores.

8. *Lift ratio*

The Lift Ratio is a measure used to evaluate the strength of an association rule derived from support and confidence values [12]. The lift ratio indicates the likelihood that when the first item is purchased, the second item will also be purchased, considering the level of support. If the lift of {X → Y} = 1, there is no association. A lift value greater than 1 indicates that item Y is more likely to be purchased if item X is purchased, whereas a value less than 1 means that item Y is less likely to be purchased if item X is purchased. The lift ratio value is calculated using the formula below [17]:

$$Lift\ ratio = \frac{Confidence\ (X,Y)}{Benchmark\ Confidence\ (X,Y)} \tag{4}$$

$$Benchmark\ Confidence\ = \frac{Nc}{N} \tag{5}$$

Where:
N = the total number of transactions in the database.
Nc = the number of transactions that contain the consequent item.

9. *Threshold*

In the Apriori algorithm, the threshold is used to set the minimum support and minimum confidence that must be met by item sets and association rules [14]. This threshold value allows researchers to determine the level of importance and the strength of the associations generated by the algorithm. By doing so, researchers can filter out irrelevant results and focus on the most significant and valuable associations.

III. Result and Discussion

The Apriori algorithm can be applied to the sales transaction data of MOY supermarket, with the accumulated sales transactions obtained from daily sales over a period of 12 days through the following stages:

A. Data Pre-processing

The data used in this research consists of transaction data that has already been organized in Microsoft Excel. Before proceeding to the data mining stage, the data undergoes pre-processing. This involves correcting any spelling errors, standardizing the format in the item name column, and categorizing the item names into more general or common item groups.

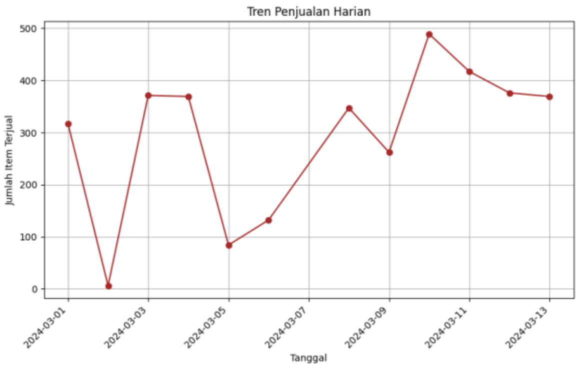

Figure 2. The Daily Sales Trends at Moy Supermarket

The graph in Figure 2. represents the daily sales trend at Moy Supermarket over a specified period. The x-axis indicates the dates, while the y-axis represents the number of items sold. The data points are connected by a line, showing the fluctuation on a sales basis. Based on Figure 2, there are noticeable ups and downs in daily sales, indicating varying consumer demand across the observed dates. On 2024-03-05, sales plummeted to a low point, reaching almost zero, suggesting an unusual drop in sales that day, which could have been due to operational challenges, lower consumer turnout, or external factors. The highest sales occurred on 2024-03-10, with a total of nearly 500 items sold. This spike could be attributed to specific promotions, events, or an increase in customer demand. Despite some sharp declines, the overall sales trend seems to rise over the observed period, suggesting a potential improvement in sales or better market conditions as the dates progress. While there are significant fluctuations in daily sales, the general upward trend provides a positive outlook for Moy Supermarket, highlighting potential opportunities for optimizing marketing strategies or better inventory management.

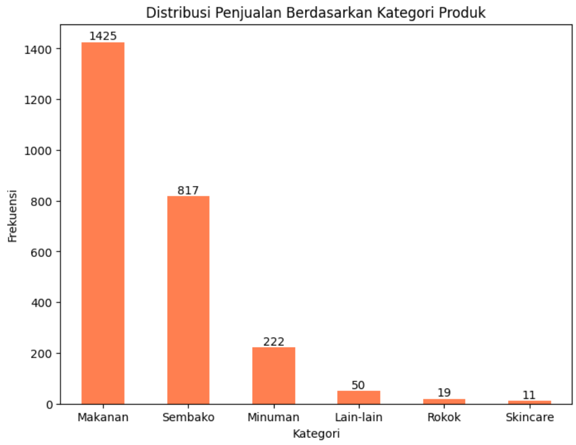

Figure 3. Sales Distribution by Product Category

The bar chart in Figure 3 illustrates the distribution of product sales at Moy Supermarket, categorized by product types. The x-axis represents the product categories, while the y-axis shows the frequency or number of items sold within each category. The height of each bar reflects the total sales for the corresponding category. The highest sales were recorded in the "Makanan" (Food) category, with 1,425 items sold. This suggests that food products are the most popular and most frequently purchased by customers. The "Sembako" (Basic Necessities) category follows with 817 items sold, indicating significant demand for essential products like rice, sugar, and oil. The "Minuman" (Beverages) category comes next, with 222 items sold, showing a moderate level of sales compared to the top two categories. Categories like "Lain-lain" (Others), "Rokok" (Cigarettes), and "Skincare" show relatively low sales, with 50, 19, and 11 items sold, respectively. These Figures indicate that these product categories are less in demand or purchased less frequently by Moy's customers. The data reflects that food and basic necessities dominate Moy Supermarket's sales, while categories like beverages, skincare, and cigarettes contribute much less to overall sales. This insight can help the supermarket adjust its inventory and marketing focus on higher-demand products to maximize sales potential.

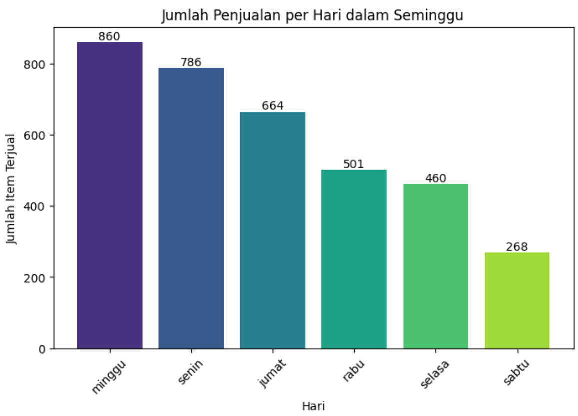

Figure 4. Total Sales per Day in a Week

The bar chart in Figure 4 illustrates the total number of items sold each day over a week at Moy Supermarket. The x-axis represents the days of the week, while the y-axis shows the number of items sold. The highest sales occurred on Sunday (Minggu), with 860 items sold, indicating that customer traffic is significantly higher on this day, possibly due to weekend shopping habits. Monday and Friday Follow Closely: Monday (Senin) and Friday (Jumat) also show substantial sales, with 786 and 664 items sold, respectively. This could indicate that shoppers are likely replenishing their supplies at the start of the week or preparing for the weekend. Sales gradually decrease as the week progresses. Wednesday (Rabu) recorded 501 items sold, followed by Tuesday (Selasa) with 460 items. These days show moderate but still steady sales activity. Saturday (Sabtu) has the lowest sales Figures, with only 248 items sold, which is in stark contrast to Sunday. This suggests that Saturday may not be a preferred shopping day for Moy's customers. The data suggests a clear pattern of higher sales on weekends, especially on Sundays, and a noticeable dip toward the end of the week, with Saturday being the least busy day. These trends could help the supermarket optimize staffing, promotions, and stock levels according to consumer shopping behaviors throughout the week.

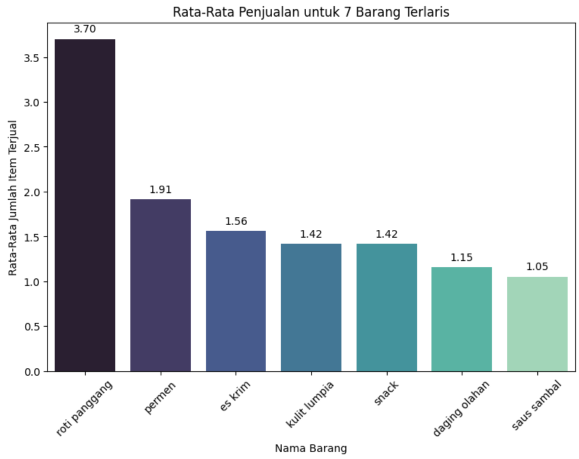

Figure 5. Average Sales for the 7 Best-Selling Products

The bar chart in Figure 5 displays the average number of items sold for the seven best-selling products at Moy Supermarket. The x-axis represents the product names, while the y-axis shows the average number of items sold per transaction. The product Roti Panggang (toast) stands out as the best-selling item with an average of 3.70 items sold per transaction. This suggests a high demand for this product, potentially making it a staple item for many customers. Following Roti Panggang are Permen (candy) with an average of 1.91 items sold and Es Krim (ice cream) with an average of 1.56 items sold. These items likely have steady demand but not as high as Roti Panggang. Kulit Lumpia (spring roll wrappers) and Susu (milk) both have an average of 1.42 items sold, showing moderate popularity. Meanwhile, Daging Cincang (minced meat) and Saus Sambal (chili sauce) have the lowest average sales with 1.15 and 1.05 items sold, respectively. The chart highlights that Roti Panggang is the top-performing product, far surpassing the other items in terms of average sales. Other products like Permen and Es Krim are also popular but are sold in fewer quantities per transaction. The insights from this data can help the supermarket focus on promoting high-performing products while adjusting inventory for lower-selling items.

B. Data Mining

1) Building Frequent Item's Results

At this stage, the researcher creates a variable consisting of several frequently purchased items. This variable is analyzed based on the transaction table in Python software using the Apriori command with a minimum support of 0.01 or 1%, resulting in item sets and their respective support values as shown in Table 1.

Table 1. Frequent Transaction Patterns of Customers

No.	Item sets	Support
1.	Frozenset({'baso aci', 'daging olahan'})	0,010256
2.	Frozenset({'mayones', 'saus sambal', 'daging olahan'})	0,010256
3.	Frozenset({'minyak goreng', 'daging olahan'})	0,010256
4.	Frozenset({'selai', 'roti panggang'})	0,010256
5.	Frozenset({'permen', 'jelly'})	0,010256
6.	Frozenset({'susu', 'permen'})	0,010256
7.	Frozenset({'susu', 'daging olahan', 'snack'})	0,011282
8.	Frozenset({'daging olahan', 'saus tomat'})	0,011282
9.	Frozenset({'bon cabe'})	0,011282
10.	Frozenset({'siomay'})	0,011282
11.	Frozenset({'bumbu', 'daging olahan'})	0,011282
12.	Frozenset({'mayones', 'saus sambal'})	0,012308
13.	Frozenset({'tusuk sate', 'daging olahan'})	0,012308
14.	Frozenset({'keripik'})	0,012308
15.	Frozenset({'permen', 'es krim'})	0,012308
16.	Frozenset({'daging olahan', 'yoghurt'})	0,013333
17.	Frozenset({'bumbu'})	0,013333
18.	Frozenset({'saus sambal', 'daging olahan', 'snack'})	0,013333
19.	Frozenset({'kulit lumpia', 'saus sambal'})	0,013333
20.	Frozenset({'tahu'})	0,014359
21.	Frozenset({'daging olahan', 'minuman rasa'})	0,014359
22.	Frozenset({'gula'})	0,014359
23.	Frozenset({'es lilin'})	0,014359
24.	Frozenset({'meses coklat 250gr'})	0,014359
25.	Frozenset({'es tube'})	0,015385
26.	Frozenset({'roti panggang', 'snack'})	0,015385
27.	Frozenset({'baso aci'})	0,015385
28.	Frozenset({'tusuk sate'})	0,015385
29.	Frozenset({'snack', 'es krim'})	0,01641
30.	Frozenset({'saus sambal', 'snack'})	0,01641
31.	Frozenset({'teh'})	0,01641
32.	Frozenset({'susu', 'snack'})	0,017436
33.	Frozenset({'donat', 'daging olahan'})	0,017436
34.	Frozenset({'saus tomat'})	0,018462
35.	Frozenset({'selai'})	0,018462
36.	Frozenset({'permen', 'daging olahan', 'snack'})	0,018462
37.	Frozenset({'masker'})	0,018462
38.	Frozenset({'jelly', 'daging olahan'})	0,019487
39.	Frozenset({'brownies', 'daging olahan'})	0,020513
40.	Frozenset({'mayones', 'daging olahan'})	0,021538
41.	Frozenset({'mie instan'})	0,021538
42.	Frozenset({'kopi'})	0,022564
43.	Frozenset({'roti panggang', 'daging olahan'})	0,022564
44.	Frozenset({'rokok'})	0,02359
45.	Frozenset({'yoghurt'})	0,024615
46.	Frozenset({'cireng', 'daging olahan'})	0,024615
47.	Frozenset({'mayones'})	0,025641
48.	Frozenset({'roti frozen', 'daging olahan'})	0,026667
49.	Frozenset({'minuman rasa'})	0,029744
50.	Frozenset({'cireng'})	0,029744
51.	Frozenset({'permen', 'snack'})	0,029744
52.	Frozenset({'brownies'})	0,030769
53.	Frozenset({'minyak goreng'})	0,030769
54.	Frozenset({'jelly'})	0,032821
55.	Frozenset({'kulit lumpia', 'daging olahan'})	0,032821
56.	Frozenset({'susu', 'daging olahan'})	0,034872
57.	Frozenset({'roti frozen'})	0,035897
58.	Frozenset({'donat'})	0,036923
59.	Frozenset({'permen', 'daging olahan'})	0,037949
60.	Frozenset({'daging olahan', 'es krim'})	0,050256
61.	Frozenset({'susu'})	0,058462
62.	Frozenset({'air mineral'})	0,066667
63.	Frozenset({'roti panggang'})	0,068718
64.	Frozenset({'daging olahan', 'snack'})	0,071795
65.	Frozenset({'permen'})	0,071795
66.	Frozenset({'saus sambal', 'daging olahan'})	0,08
67.	Frozenset({'es krim'})	0,094359
68.	Frozenset({'saus sambal'})	0,104615
69.	Frozenset({'kulit lumpia'})	0,121026
70.	Frozenset({'snack'})	0,140513
71.	Frozenset({'daging olahan'})	0,526154

Support value refers to the percentage of the average popularity of a product or item in the dataset. With a minimum support value of 0.01 or 1%, a buyer (consumer) who purchases one item or multiple items together will have a certain support value. For example, in the first row of Table 1, a consumer who buys 250g of chocolate sprinkles will only purchase that item, where 1.02% of the transactions in the database contain only the 250g chocolate sprinkles.

2) *Association Rule*

The determination of support and confidence in this study is based on a minimum threshold where the lift ratio metric is set to 1. A filter is then applied, requiring a minimum lift ratio of 1.5 and a minimum confidence level of 0.5 or 50%, which results in six association rules, as detailed in Table 2.

Table 2. Association Rules Result

No.	Antecedents	Consequents	Support
1.	Frozenset({'Bumbu})	Frozenset({'Daging Olahan'})	0.011282
2.	Frozenset({'Mayones'})	Frozenset({'Daging Olahan'})	0.021538
3.	Frozenset({'Saus Sambal, Mayones'})	Frozenset({'Daging Olahan'})	0.010256
4.	Frozenset({'Cireng'})	Frozenset({'Daging Olahan'})	0.024615
5.	Frozenset({'Snack, Saus Sambal'})	Frozenset({'Daging Olahan'})	0.013333
6.	Frozenset({'Tusuk Sate })	Frozenset({'Daging Olahan'})	0.012308
7.	Frozenset({'Selai'})	Frozenset({'Roti Panggang })	0.010256

Table 2 above presents the association rules derived from the dataset at Moy Supermarket. The goal is to identify products that are frequently purchased together. Each rule represents an antecedent (the product or set of products) and a consequent (the product likely to be purchased together). The support value quantifies the proportion of transactions that contain both the antecedent and the consequent.

Frequent Co-Purchases with Processed Meat: Several antecedents, such as Bumbu (seasoning), Mayones (mayonnaise), Saus Sambal (chili sauce), Cireng, Snack, and Tusuk Sate (satay skewers), lead to the purchase of Daging Olahan (processed meat). The support values for these associations range between 0.010256 and 0.024615, indicating that in 1.03% to 2.46% of transactions, these products are bought together with processed meat. Cireng has the highest support (0.024615), suggesting that customers who purchase Cireng are more likely to also buy processed meat. The combination of Snack and Saus Sambal has a support of 0.013333, highlighting a notable association with processed meat.

The combination of Saus Sambal and Mayones has a support value of 0.010256, indicating that around 1% of transactions involve the purchase of both sauces, which also leads to the purchase of processed meat. This may suggest that these sauces are often used together with processed meat for meal preparation.

There is a notable rule showing that customers who purchase Selai (jam) are likely to also buy Roti Panggang (toast). This rule has a support of 0.010256, meaning that in around 1.03% of transactions, both jam and toast are bought together. This reflects a common combination of items typically consumed as a breakfast or snack.

The association rules provide valuable insights into consumer behavior at Moy Supermarket. The rules suggest that processed meat is often bought alongside condiments and related items like Cireng and Tusuk Sate. Additionally, there is a strong relationship between Selai and Roti Panggang, reflecting common consumption patterns. These findings can help the supermarket optimize product placements, bundle promotions, or cross-selling strategies to enhance sales.

Table 3. Confidences Association Rules

Antecedents	Consequents	Confidence
frozenset({'cireng'})	frozenset({'daging olahan'})	0,85185
frozenset({'saus sambal', 'snack'})	frozenset({'daging olahan'})	0,83333
frozenset({'mayonais'})	frozenset({'daging olahan'})	0,76471
frozenset({'saus sambal'})	frozenset({'daging olahan'})	0,75949
frozenset({'ilm tempura 500gr '})	frozenset({'daging olahan'})	0,73077
frozenset({'selai'})	frozenset({'roti frozen'})	0,55556
frozenset({'permen', 'daging olahan'})	frozenset({'snack'})	0,5

Table 3 is the result of association rule mining which displays the relationship between products in purchase transactions. Each line shows the association rule with antecedents (initial purchase items), consequents (items that tend to be purchased together), and confidence ("if-then" condition probability). The first frozenset rule showed that if a customer bought Cireng, there was an 85.19% chance that they would also buy Daging Olahan (processed meat), indicating a very strong relationship. A similar pattern can be seen in the combination of Saus Sambal and Snack that have a high impetus for the purchase of Daging Olahan. Meanwhile, the rules of frozenset ({'mayonnaise'}) → frozenset ({'daging olahan'}) with a confidence of 76.47% and frozenset ({'saus sambal'}) → frozenset ({'daging olahan'}) with a confidence of 75.95% still showed a significant correlation although slightly lower. On the other hand, Selai and Roti Frozen with a confidence of 55.56% revealed a moderate relationship, while frozenset({'permen', 'daging olahan'}) → frozenset ({'snack'}) with a confidence of 50% indicated a weaker relationship, where only half of the transactions followed this pattern. This analysis is useful for marketing strategies such as placing products adjacent to each other or bundling discounts based on dominant purchasing patterns.

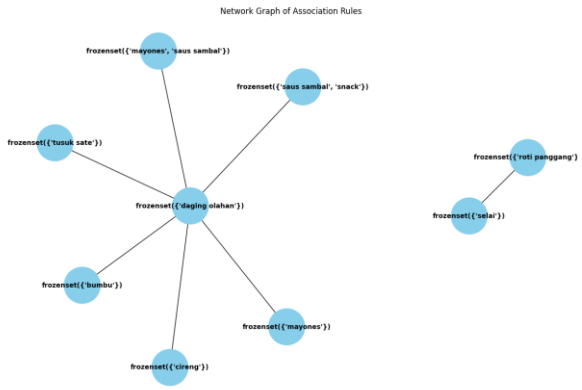

Figure 6. *Network Graph of Association Rules*

The image in Figure 6 above represents a network graph of the association rules derived from consumer transaction data at Moy Supermarket. The graph visualizes the relationships between products (as nodes) based on the association rules, with lines (edges) indicating co-purchase patterns. Daging Olahan (processed meat) appears as the central node in the graph with multiple connections to other product sets. This indicates that processed meat is frequently purchased together with various other products. Products like Bumbu (seasoning), Mayones (mayonnaise), Saus Sambal (chili sauce), Tusuk Sate (satay skewers), Cireng, and the combination of Snack with Saus Sambal all connect to processed meat, reinforcing the high likelihood of co-purchases involving these products.

The combination of Saus Sambal and Mayones forms a node that links to Daging Olahan, suggesting that these two products are often bought together, potentially as accompaniments to processed meat. Another notable combination is Snack and Saus Sambal, which also connects to processed meat. In a separate cluster, Roti Panggang (toast) is connected with Selai (jam), indicating a strong association between these two products. This cluster is isolated from the processed meat cluster, showing that these products form their own distinct co-purchase pattern.

The network graph effectively visualizes the strong relationships between processed meat and various condiments or side dishes, reflecting consumer preferences for meal preparation. The connection between Selai and Roti Panggang in a separate cluster suggests a different type of consumer behavior, likely centered around breakfast or snack items. These insights can help Moy Supermarket strategically organize product placements and cross-promotions, enhancing customer experience and boosting sales through co-purchase tendencies.

IV. Conclusions

A. Conclusions

Based on the analysis conducted in this study, the following conclusions can be drawn:

1. The association rule-mining method using the Apriori algorithm can help supermarkets identify consumer shopping patterns.
2. The results of the Apriori algorithm analysis using a dataset of 2,544 transactions produced the following association rules:
   - When customers buy spices, they also purchase processed meat, and they are 85% confident in the products they buy simultaneously.
   - When customers buy mayonnaise, they purchase preserved processed meat with reliable product quality, and the likelihood of buying these products together increases by 84%.
   - When customers buy chilli sauce and mayonnaise, they purchase processed meat with an 83% confidence level in what product they will buy simultaneously.
   - When customers buy cireng (fried dough), they purchase snacks and processed meat with an 83% confidence level for buying these products together.
   - When customers buy snacks and chili sauce, they purchase processed meat with an 81% confidence level regarding the products they buy simultaneously.
   - When customers buy skewers, they purchase processed meat with an 80% confidence that these products will be purchased together.
   - When customers buy jam, they purchase frozen or toasted bread with a 55% confidence level regarding the products they will buy simultaneously.

B. Recommendations

After identifying consumer shopping patterns, MOY Supermarket can stock more items such as spices, chili sauce, mayonnaise, snacks, jam, frozen bread, cireng (fried dough), skewers, and processed meat to avoid stock shortages. On the other hand, MOY Supermarket should reduce stock for items that are rarely purchased to prevent overstocking. MOY Supermarket can implement sales strategies such as offering discounts or promotions on product bundles that are likely to be purchased together and offering complementary products.

Recommendations for future research include using a larger dataset and applying the Apriori algorithm with a higher minimum support threshold. Future studies are also encouraged to use other algorithms for association rule-mining and compare them to determine which algorithm is more accurate.

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