

## Research Article

# Implementation of Apriori and Fp-Growth Algorithms in Analyzing Sales Patterns on Sekojab's Moving Coffee

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## ABSTRACT

Advances in information technology have encouraged the use of sales data as a strategic source of information for micro-enterprises. Kopi Keliling Sekojab, a micro-enterprise, generates sales transaction data that has the potential to be analyzed to identify consumer purchasing patterns. However, this data is generally used for administrative purposes without in-depth analysis. This study aims to analyze sales patterns at Kopi Keliling Sekojab by implementing the Apriori and FP-Growth algorithms. The research method used is data mining with a quantitative approach, through the Knowledge Discovery in Database (KDD) stages, which include data collection, pre-processing, data transformation, algorithm application, and analysis of the results. The analyzed data consisted of 30 sales transactions, which were processed to determine support and confidence values to form association rules. The results show that the Apriori and FP-Growth algorithms are capable of identifying customer purchasing patterns, with FP-Growth generating more and more efficient association rules than Apriori. The obtained patterns can be utilized by Kopi Keliling Sekojab businesses in developing sales strategies, stock management, and data-driven service improvements

**Keywords:** Data Mining; Apriori; FP-Growth; Sales Pattern; Mobile Coffee

## 1. INTRODUCTION

Development information technology has brought significant changes in various sectors, including field trade and business micro. The sales data generated from activity business Every day it no longer only functions as a transaction archive, but also as a source of strategic information that can be used to improve performance. business. Unfortunately, many perpetrator business small Still utilize sales data only recording administrative without further analysis.

Sekojab Mobile Coffee is one of the business sufficient micro developing in Rantauprapat. Sales activities carried out every day generates relatively accurate transaction data numerous and varied. The data has the potential reveal Customer purchasing patterns, such as product combinations frequently purchased together. This information can be used to improve promotional strategies, inventory management, and stock, and menu arrangement.

Data mining is techniques that can be used to dig up hidden information from large data sets. One of popular data mining methods is Association Rule Mining, which aims to find relationships between items in a transaction. The Apriori and FP-Growth algorithms are two algorithms that are widely used to find patterns. association. A priori is known as the concept support and confidence, meanwhile FP-Growth offers better efficiency by utilizing FP-Tree structure. FP-Growth is an alternative algorithm for discovering frequent itemsets in transactional datasets (Khadijah & Waluyo, 2024). Comparative studies have shown that the performance of FP-Growth and Apriori can be compared in terms of processing time and memory usage when generating association rules (Raihan et al., 2024).

Based on the broader policy perspective, implementation refers to the stage at which a policy is translated into concrete action (Yuliah, 2020). Based on this context, the present study examines the implementation of the Apriori and FP-Growth algorithms to analyze sales patterns at Sekojab Mobile Coffee and to support data-based decision making.

## Theoretical Basis

### Knowledge Discovery in Databases (KDD)

Knowledge Discovery in Databases (KDD) is a method used to discover previously unknown knowledge or information from databases (Hidayat et al., 2024). KDD includes a series of activities involving the collection and use of historical data to identify regularities, patterns, and relationships in large datasets (Henando, 2020). In general, the stages of KDD include data cleaning, data integration, data selection, data transformation, data mining, and the evaluation and presentation of knowledge.

## Data Mining

Data mining is the process of extracting valuable information from large datasets (Claudia et al., 2024). As a data-processing approach, data mining enables data to be used as a strategic source of information (Musdalifah & Jananto, 2022). In a business context, data mining plays an important role in understanding consumer behavior and supporting strategic decision making.

### Apriori Algorithm

The Apriori algorithm is a well-known method for finding frequent itemsets through association rule techniques (Harahap et al., 2022). In data mining, Apriori is widely used to identify associations among attributes or items in transaction data, which is often referred to as affinity analysis or market basket analysis (Chailes et al., 2020). The algorithm works iteratively by generating candidate itemsets and pruning those that do not meet the minimum support threshold.

### FP-Growth Algorithm

Frequent Pattern Growth (FP-Growth) is a method used to identify frequent itemsets in a dataset (Mahtum & Fatah, 2024). FP-Growth was developed to address the limitations of Apriori, especially for larger datasets, by using an FP-Tree structure to store transaction information without repeatedly generating candidate itemsets.

### Sales Pattern

Sales patterns refer to relationships or trends in sales transaction data that can be analyzed to understand consumer behavior and product preferences (Davelino et al., 2025). In line with the increasing coffee consumption in Indonesia, mobile coffee trading has grown rapidly (Tiara et al., 2025). Therefore, sales pattern analysis can help business actors determine promotional strategies, manage stock, and predict demand.

### Supporting Tools

Microsoft Excel is a spreadsheet application that can be used to display data, perform calculations, process numerical information, and prepare reports (Rianti & Harahap, 2021). After the data were transformed into a binary tabular format, the analysis and testing stages were conducted using RapidMiner software (Junaidi, 2019). RapidMiner is a data analytics platform that facilitates performance comparison between algorithms (Julianto et al., 2020).

## 2. RESEARCH METHOD

This study used a quantitative approach with data mining methods. The data consisted of sales transactions from Kopi Keliling Sekojab during a specific period. Because the population size was not identified with certainty, the researchers applied a non-probability sampling approach using purposive sampling, namely selecting consumers who had purchased Sekojab Mobile Coffee products either online or offline (Pratama et al., n.d.).

The research stages include transaction data collection, data pre-processing, data transformation, application of the Apriori algorithm, implementation of the FP-Growth algorithm, and analysis and comparison of results.

1. Transaction data collection
2. Data pre-processing
3. Data transformation
4. Application of the Apriori algorithm
5. Implementation of the FP-Growth algorithm
6. Analysis and comparison of results

Data pre-processing was carried out by removing duplicate data, correcting recording errors, and converting the data into a binary transaction table ready for analysis. This stage was followed by data selection, namely preparing a custom table structure that integrates attributes from several sources in the internal information system to form the dataset used in the analysis (Wadanur & Sari, 2022).

## 3. RESULTS AND DISCUSSION

### 3.1 Results of Applying the Apriori Algorithm

Data selection is the stage in which a custom table structure is prepared and populated with attributes from several tables in the internal information system so that the dataset can be analyzed (Hidayat et al., 2024). In this study, the next step was to prepare the dataset for analysis.

**Table 1.** Description Initials

Menu Name	Code
Kojab Coffee (strong)	KC
Kojar Coffee (soft)	KCS
Caramel Coffee	CC
Pandan Coffee	PC
Banana Coffee	BC
Butterscotch Coffee	BSC
Matcha	M
Taro	T
Chocolate	C
Red Velvet	RV
Bread	R
Nuggets	N
Salad	S
French fries	KG

Source: Research, 2025

Transaction data obtained from in internal application for selling Mobile Coffee in Sekojab Rantauprapat and from transaction the 13 data were obtained from 30 days for period of October 2025 such as **Table 1**. At the stage This is stage *pre-processing on* existing data processed in stages previously. At this stage This will he did search for existing missing *value* data selected previously. Stage Transformation is a process of changing data with the aim of for make things easier processing and analysis of the data used. In this process do changes into tabular data format. Each item is listed in **Table 2**.

**Table 2.** Sales Transaction

Transaction	Item List
T1	KC, CC, PC, M, T, R, N, KG
T2	KC, PC, BC, M, T, R, N, KG
T3	KC, PC, M, T, R, N, S, KG
T4	KC, PC, BC, M, T, S, KG
T5	KC, PC, M, T, S
T6	KC, CC, PC, BC, BSC, M, S
T7	KC, PC, BSC, N, S
T8	KC, BC, BSC, S
T9	KC, CC, BSC, R, S, KG
T10	KC, KCS, CC, BC, BSC, RV, S
T11	KC, KCS, CC, BC, BSC, T, RV, N, S, KG
T12	KC, KCS, CC, BC, BSC, T, RV, R, N
T13	KC, KCS, CC, BC, BSC, T, RV, N
T14	KC, KCS, CC, BC, BSC, RV, N, KG
T15	KC, KCS, BC, RV, R, N
T16	KC, R, N
T17	KC, R, N, KG
T18	KC, KCS, M, RV, R, N
T19	KC, KCS, M, RV, N
T20	KC, KCS, T, RV
T21	KC, KCS, T, RV
T22	KC, KCS, PC, RV
T23	KC, KCS, PC, RV, S
T24	KC, CC, PC, R
T25	KC, R, N
T26	KC, N
T27	KC, KCS, RV
T28	KC, KCS, RV, R
T29	KC, KCS, M, RV
T30	KC, CC, M

Source: Research, 2025

**Table 3.** Tabular Data

Transaction	KC	KCS	CC	PC	BC	BSC	M	T	RV	R	N	S	KG
1	1	0	1	1	0	0	1	1	0	1	1	0	1
2	1	0	0	1	1	0	1	1	0	1	1	0	1
3	1	0	0	1	0	0	1	1	0	1	1	1	1
4	1	0	0	1	1	0	1	1	0	0	0	1	1
5	1	0	0	1	0	0	1	1	0	0	0	1	0
6	1	0	1	1	1	1	1	0	0	0	0	1	0
7	1	0	0	1	0	1	0	0	0	0	1	1	0
8	1	0	0	0	1	1	0	0	0	0	0	1	0
9	1	0	1	0	0	1	0	0	0	1	0	1	1
10	1	1	1	0	1	1	0	0	1	0	0	1	0
11	1	1	1	0	1	1	0	1	1	0	1	1	1
12	1	1	1	0	1	1	0	1	1	1	1	0	0
13	1	1	1	0	1	1	0	1	1	0	1	0	0
14	1	1	1	0	1	1	0	0	1	0	1	0	1
15	1	1	0	0	1	0	0	0	1	1	1	0	0
16	1	0	0	0	0	0	0	0	0	1	1	0	0
17	1	0	0	0	0	0	0	0	0	1	1	0	1
18	1	1	0	0	0	0	1	0	1	1	1	0	0
19	1	1	0	0	0	0	1	0	1	0	1	0	0
20	1	1	0	0	0	0	0	1	1	0	0	0	0
21	1	1	0	0	0	0	0	1	1	0	0	0	0
22	1	1	0	1	0	0	0	0	1	0	0	0	0
23	1	1	0	1	0	0	0	0	1	0	0	1	0
24	1	0	1	1	0	0	0	0	0	1	0	0	0
25	1	0	0	0	0	0	0	0	0	1	1	0	0
26	1	0	0	0	0	0	0	0	0	0	1	0	0
27	1	1	0	0	0	0	0	0	1	0	0	0	0
28	1	1	0	0	0	0	0	0	1	1	0	0	0
29	1	1	0	0	0	0	1	0	1	0	0	0	0
30	1	0	1	0	0	0	1	0	0	0	0	0	0

Source: Research, 2025

In the data mining stage, the steps First is to determine which items will be used in manual calculations by means count minimum support value per item where later the item that has mark support below the minimum limit will be written off or not used and the following method count Support and examples:

$$Support(A) = \frac{\text{The number of transactions containing } A}{\text{Total Transactions}} \times 100\%$$

$$Support(KC) = \frac{30}{30} \times 100\% = 100\%$$

This study establishes that the minimum support used is 50% as in **Table 4**.

**Table 4.** Support for Each Item

Item	Amount	Support (%)	Support (%)	Information
KC	30	(30/30)	100%	Fulfil
KCS	15	(15/30)	50%	Fulfil
CC	10	(10/30)	33.30%	Does not meet the
PC	10	(10/30)	33.30%	Does not meet the
BC	10	(10/30)	33.30%	Does not meet the
BSC	9	(9/30)	30%	Does not meet the
M	10	(10/30)	33.30%	Does not meet the
T	10	(10/30)	33.30%	Does not meet the
RV	15	(15/30)	50%	Fulfil
R	12	(12/30)	40%	Does not meet the
N	15	(15/30)	50%	Fulfil
S	10	(10/30)	33.30%	Does not meet the
KG	8	(8/30)	26.6%	Does not meet the

Source: Research, 2025

After setting the minimum support of 50% as in **Table 4**, next will done combination of 2 item parts to get minimum support of 50% as in **Table 5**.

$$Support(A,B) = \frac{\text{The number of transactions containing } A,B}{\text{Total Transactions}} \times 100\%$$

$$Support(KC, KCS) = \frac{15}{30} \times 100\% = 50\%$$

**Table 5.** Combination of 2 Items

Item	Amount	Support (%)	Support (%)	Information
KC, KCS	15	(15/30)	50%	Fulfil
KC, RV	15	(15/30)	50%	Fulfil
KC, N	15	(15/30)	50%	Fulfil
KCS, RV	15	(15/30)	50%	Fulfil
KCS, N	7	(7/30)	23.30%	Does not meet the
RV, N	7	(7/30)	23.30%	Does not meet the

Source: Research, 2025

After set a minimum support of 50% as in **Table 5**, then will done combination of 3 part items to get minimum support of 75% as in **Table 6**.

$$Support(A, B, C) = \frac{\text{The number of transactions containing } A, B, C}{\text{Total Transaction}} \times 100\%$$

$$Support(KC, KCS, RV) = \frac{15}{30} \times 100\% = 50\%$$

**Table 6.** Combination of 3 Items

Item	Amount	Support (%)	Support (%)	Information
KC, KCS, RV	15	(15/30)	50%	Fulfil
KC, KCS, N	7	(7/30)	23.30%	Does not meet the
KCS, RV, N	7	(7/30)	23.30%	Does not meet the

Source: Research, 2025

Based on the **Table 6**, the combination data from three categories that meet over threshold of 50% is three data, namely KC, KCS, RV therefore iteration stopped. Next step after determine support from combination category is count confidence. To find rule association A minimum confidence of 70% is also required, with use formula confidence calculation, then the data obtained is as in **Table 7**.

Formula count confidence that is:

$$Confidence = \frac{\sum \text{The number of transactions containing } A \text{ and } B}{\sum \text{Transaction } A} \times 100\%$$

$$Confidence = \frac{\sum 50}{\sum 50} \times 100\%$$

**Table 7.** Calculation Results of Confidence

Antecedent, Consequent	Support (%)	Confidence Calculation	Confidence
KC, KCS	50%	(50*100/50)	100
KCS, KC	50%	(50*100/100)	50
KC, RV	50%	(50*100/50)	100
RV, KC	50%	(50*100/100)	50
KC, N	50%	(50*100/50)	100
N, KC	50%	(50*100/100)	50
KCS, RV	50%	(50*100/50)	100
RV, KCS	50%	(50*100/100)	50
KC, KCS, RV	50%	(50*100/50)	100
KC, RV, KCS	50%	(50*100/100)	50
RV, KCS, KC	50%	(50*100/50)	100

Source: Research, 2025

**Table 8.** Items that Meet Minimum Confidence

Antecedent, Consequent	Confidence
Kojab Coffee, Kojar Coffee	100
Kojab Coffee, Red Velvet	100
Kojab Coffee, Nuget	100
Kojar Coffee, Red Velvet	100
Kojab Coffee, Kojar Coffee, Red Velvet	100
Red Velvet, Kojar Coffee, Kojab Coffee	100

Source: Research, 2025

### 3.2 Results of the FP-Growth Algorithm

On the side other, algorithm FP-Growth offers a more approach efficient. In the method FP-Growth if referring to the data in **Table 2**, then can created transaction data in a way descending as in **Table 9**.

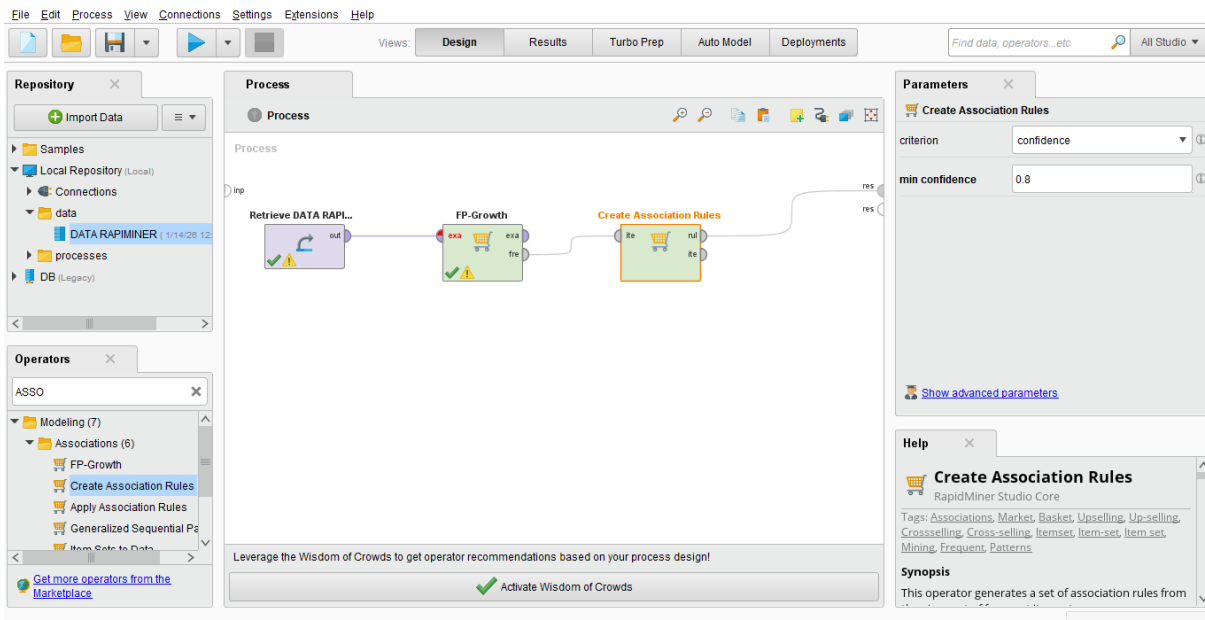
**Table 9.** Item Appearance Sorted Based on Frequency Highest

Item	Amount
KC	30
KCS	15
RV	15
N	15
R	12
CC	10
PC	10
BC	10
M	10
T	10
S	10
BSC	9
KG	8

Source: Research, 2025

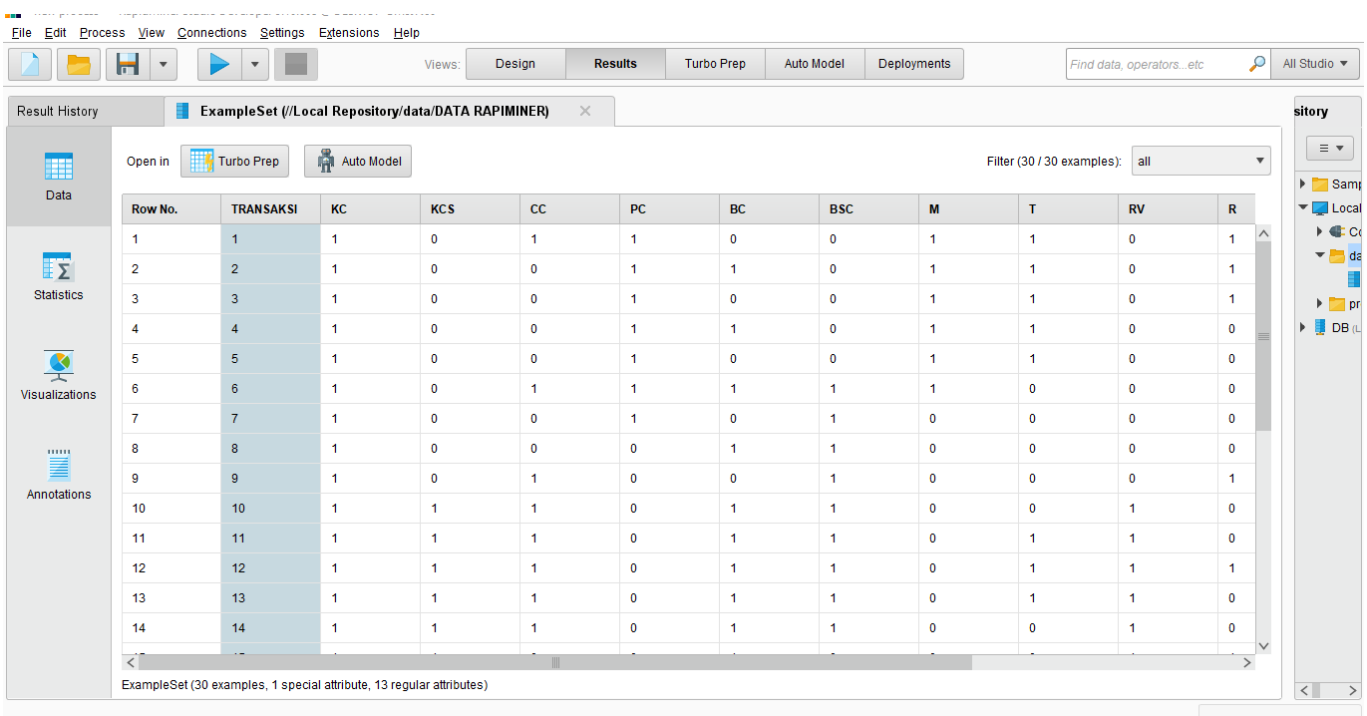
After it is done sorting, obtained items that have frequency emergence above the minimum support limit that has been determined, so that the item is stated as a frequent item and used in the formation process. FP-Tree, items with frequency highest is Kojab Coffee (KC), followed by Kojar Coffee (KCS), Redvelvet (RV), and Nuget (N). These items are the basis for the search process. Frequent patterns and formation rule association using the FP-Growth algorithm.

With using RapidMiner 9.10 software, the process steps for algorithm *FP-Growth* can depicted as following:



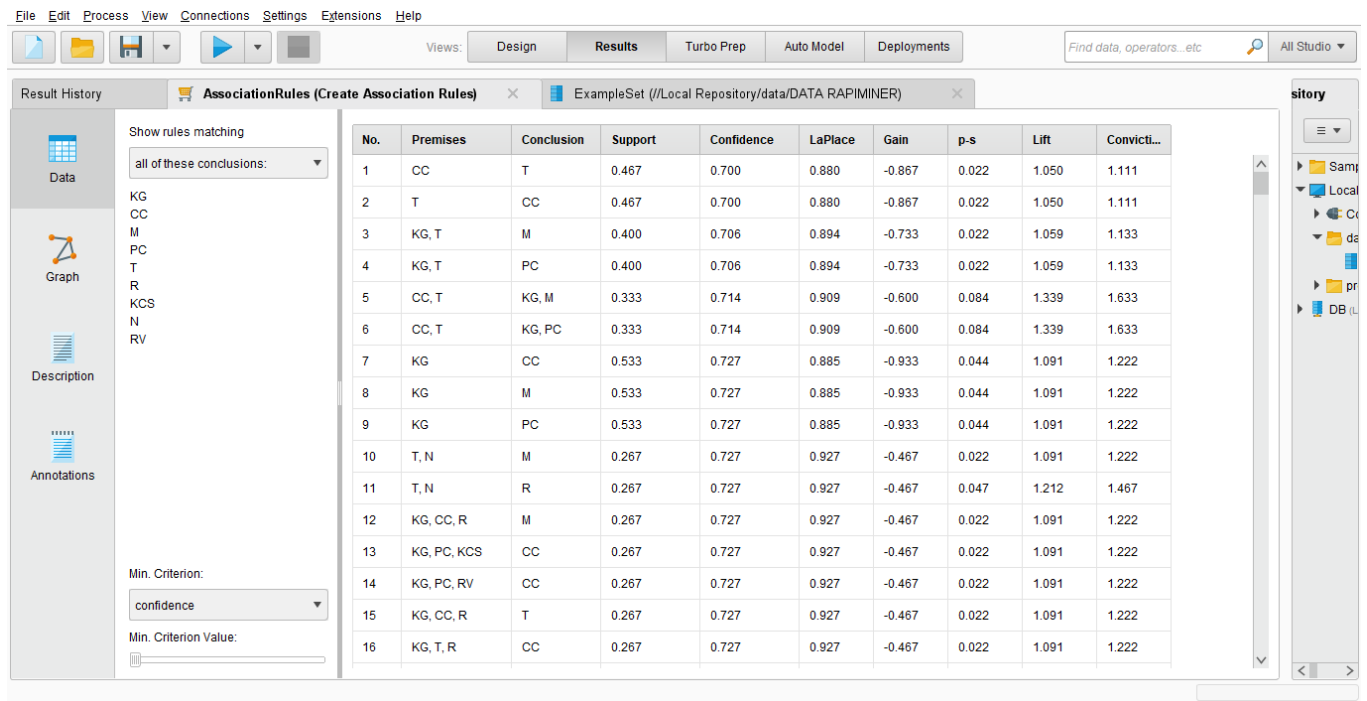
Source: Research, 2025

**Figure 1.** FP-Growth on RapidMiner



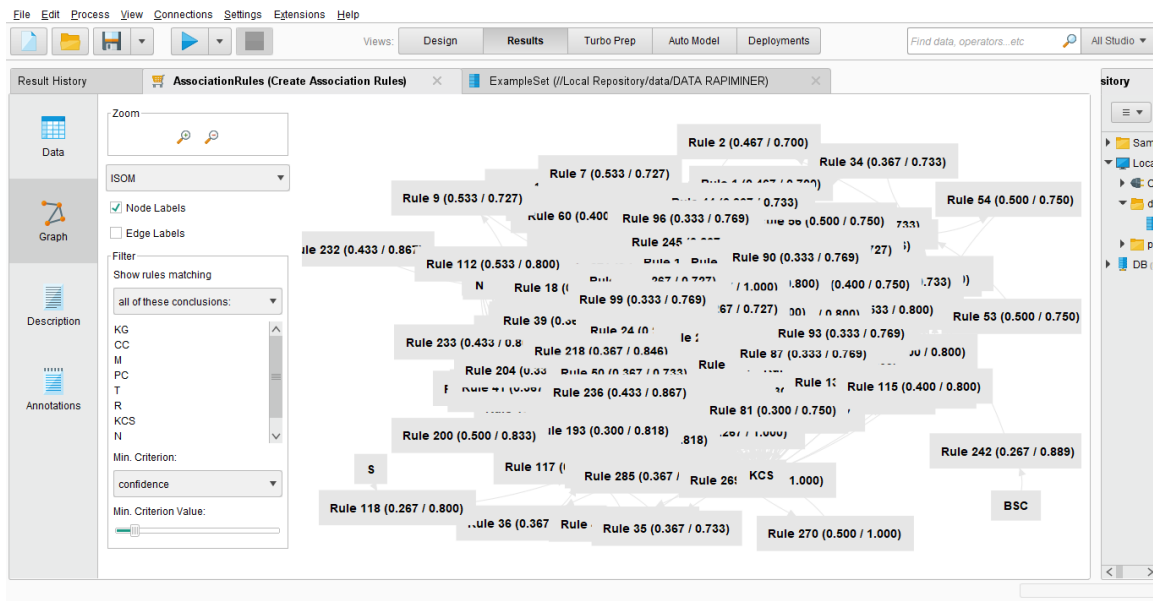
Source: Research, 2025

Figure 2. Numerical to Binominal process of sales data sample



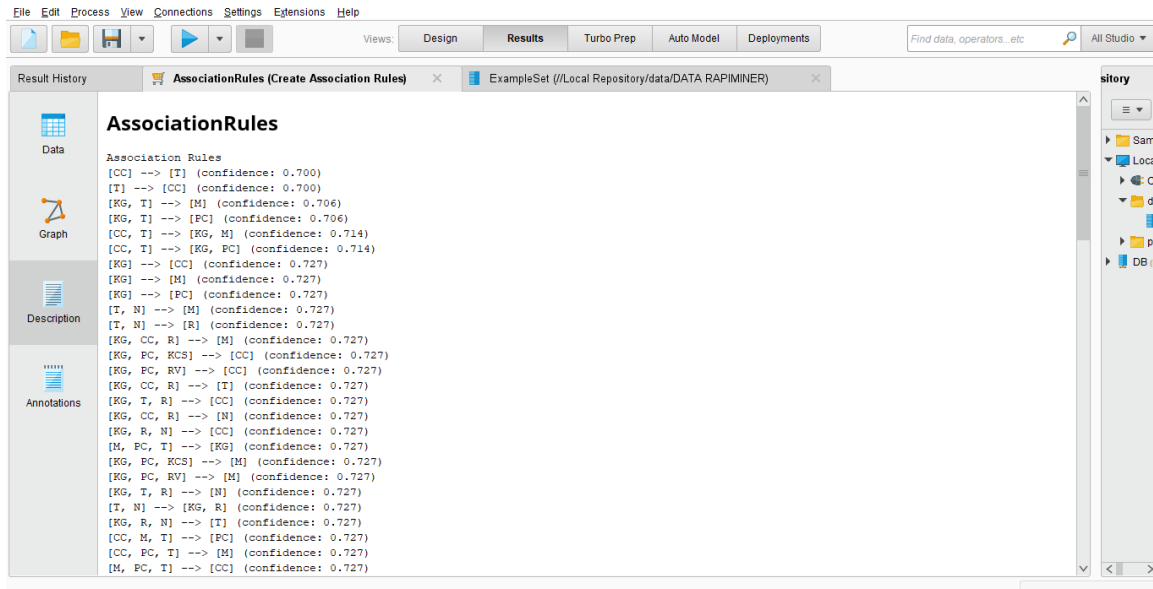
Source: Research, 2025

Figure 3. Support and Confidence using RapidMiner from sales data samples



Source: Research, 2025

Figure 4. Graphic Rule sample sales data using RapidMiner



Source: Research, 2025

Figure 5. Association Rules from RapidMiner

From the processing of sales data in Figure 4, the calculation process is carried out using RapidMiner obtained amount rule association as many as 337 rules with the lowest support is 20% and the highest is 56%, while lowest confidence is 70% and the highest is 100%.

### 3.3 Discussion

The findings demonstrate that both Apriori and FP-Growth can identify meaningful co-purchase patterns in Sekojab Mobile Coffee transaction data. In the Apriori analysis, Kojab Coffee (KC), Kojar Coffee (KCS), Red Velvet (RV), and Nuggets (N) met the minimum support threshold of 50%, indicating that these menu items formed the most consistent combinations in customer purchases. This result confirms that association rule mining can transform routine transaction records into actionable insights for business decision making (Hidayat et al., 2024).

The Apriori results also produced several association rules with 100% confidence, especially among KC, KCS, and RV. High-confidence rules indicate that the presence of one item is followed very consistently by the presence of another item in the same transaction. For small businesses, this pattern is useful for designing bundled products, arranging cross-selling strategies, and planning inventory more accurately. Similar studies have shown that Apriori is effective for producing clear

and interpretable purchasing rules, particularly when the objective is to support practical managerial decisions (Wadanur & Sari, 2022). However, the present study also highlights the main limitation of Apriori. Because the algorithm generates candidate itemsets repeatedly at each iteration, the computational process becomes less efficient as the number of transactions and item combinations increases. This weakness has been reported in previous comparative studies, which found that Apriori generally requires more processing time and memory than FP-Growth when applied to larger or denser datasets (Raihan et al., 2024).

In contrast, FP-Growth produced 337 association rules with support values ranging from 20% to 56% and confidence values from 70% to 100%. These results indicate that FP-Growth was able to uncover more varied purchasing combinations than Apriori while maintaining strong rule quality. This advantage is related to the FP-Tree structure, which compresses transaction data efficiently and avoids repeated candidate generation. Therefore, the findings support earlier studies showing that FP-Growth is more efficient and more comprehensive than Apriori for market basket analysis and transactional data exploration (Mahtum & Fatah, 2024). Overall, the comparison suggests that Apriori is beneficial when researchers or business owners need simple and transparent association rules, whereas FP-Growth is more appropriate when the goal is to generate a richer rule set with better computational efficiency. For Sekojab Mobile Coffee, these findings can be translated into promotional packages, menu pairing recommendations, and stock planning based on actual customer preferences. Such data-driven decisions are especially important for mobile coffee businesses operating in competitive markets and needing adaptive marketing strategies to maintain customer interest and improve sales performance (Kurniawan & Madiistriyatno, 2023). Results of the FP-Growth Algorithm

#### 4. CONCLUSION

Based on the research results, it can be concluded that both the Apriori and FP-Growth algorithms are capable of identifying sales patterns in Sekojab Mobile Coffee. These two algorithms can be used to discover relationships among products that frequently appear together in transactions, making consumer purchasing patterns easier to understand. Through these patterns, the business can identify which products are commonly purchased simultaneously by customers. This finding shows that the application of data mining, especially association analysis, plays an important role in transforming sales data into useful information for business decision-making. In addition, the results indicate that the FP-Growth algorithm is more efficient than the Apriori algorithm in terms of computation time. This suggests that FP-Growth has an advantage in processing transaction data more quickly and efficiently. Such efficiency is particularly beneficial for a mobile coffee business like Sekojab, as faster data processing can help the business owner respond to market needs more effectively. Therefore, the results of the analysis not only describe sales patterns but can also serve as a basis for improving sales strategies, such as creating product bundles, designing promotions, and managing inventory according to customer purchasing habits. For future research, it is recommended to use a larger dataset so that the analysis results become more accurate and representative. Furthermore, future studies may combine association algorithms with other data mining methods in order to produce deeper analysis and provide more comprehensive business strategy recommendations.

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