

FP-Growth Algorithm for Association Model Optimization in Household Sales Data

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Abstract

This research aims to find the value of support and confidence parameters needed so that associations between products can be identified and get the value of support, confidence, lift for the association rules found, and identify products that have the highest support value in frequent itemsets. The method used is Knowledge Discovery in Databases (KDD) with the stages of data collection, data pre-processing, data transformation, data mining, dan interpretation and evaluation. Sales transaction data was collected from January 1 to September 30, 2024, focusing on support and confidence values. The results showed that the association was successfully found with a parameter value of support 0.02 and confidence 0.5. In the association found, the products SWEAT BRONZE PANTS MINI M5 and SWEAT BRONZE PANTS MINI L5 have a support value of 0.004, confidence of 0.073, and lift of 1.421. These values indicate that although the frequency of this association is low, its strength exceeds that of a random association, which can be used in marketing strategies like product bundling. The product "SENSI PEREKAT S20" has the highest support of 0.149 (14.9%). The findings provide insight into the use of data mining algorithms to design data-driven marketing strategies and more efficient inventory management.

Keywords: Association Rules; Data Mining; FP-Growth; Knowledge Discovery in Databases; Purchasing Patterns

1. Introduction

Technological advances are currently developing very rapidly, having a significant impact on various sectors in this digital era, including industry, business, information, and other sectors [1]. Research shows that big data analytics can significantly increase sales growth, highlighting the importance of data utilization in business strategy [2]. In general, data mining is the process of finding patterns or information useful for large and complex data-based decision making [3]. One of the growing approaches in data analysis is the application of association models using the FP-Growth algorithm, which aims to identify patterns of relationships between products in transaction data and has proven effective in optimizing business strategies and improving operational efficiency [4]. In data mining, association is a method to find interesting relationships or linkages between items in a dataset, which is usually used to formulate a more focused marketing strategy [5]. This association model not only helps in understanding consumer behavior, but also allows companies to design more targeted marketing [6].

The main challenges in sales data association include the accuracy of identifying relevant patterns and the speed of data processing [7]. According to [8], the complexity of information systems in sales data management often slows down the analysis and decision-making process. To achieve optimal analysis, an in-depth understanding of the various factors that influence consumer behavior is required [9]. In this case, the main problem faced by stores is how to find patterns or relationships between products that are often bought together by customers, which can be used to improve sales and shopping experience.

This research aims to optimize the FP-Growth algorithm model in analyzing consumer purchase patterns on sales data in household goods stores, focusing on three main objectives. First, this research aims to obtain the value of the support and confidence parameters to make an association from the sales data. Second, this research aims to obtain the support and confidence values for the association rules found. Thirdly, this research will identify the products that have the highest support values, which can provide insights in planning more effective strategies.

In this research, the approach used is the Knowledge Discovery in Databases (KDD) method with the FP-Growth algorithm to analyze association patterns in sales transaction data. The FP-Growth algorithm was chosen because of its ability to extract hidden patterns from large data efficiently, without requiring repeated scans of the database, thus speeding up the analysis process [10]. FP-Growth is an improvement of the Apriori algorithm which is more efficient in processing large data and is able to find recurring patterns without the need to explicitly generate candidates [11]. Fp-Growth is an appropriate algorithm to describe customer purchase patterns and items that are often purchased together [12]. The results of this research are expected to make a significant contribution to understanding the analysis of consumer purchasing patterns in the field of Informatics, especially by using the FP-Growth algorithm to process large and

complex sales data. The research is expected to find recurring purchase patterns and relationships between products that may have been previously hidden in the data.

2. Research Methods

In this research, the method used is a quantitative method with a Knowledge Discovery in Databases (KDD) approach to identify association patterns between products in sales transaction data using the FP-Growth algorithm. Quantitative methods are used because they are able to provide objective results through numerical data processing and in-depth statistical analysis. With this approach, data can be processed in a structured manner so that the relationship patterns between products can be seen more clearly and accurately. The research method used in the study as shown in Figure 1.

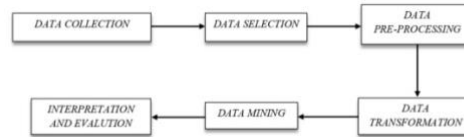


Figure 1: Research Methods

2.1. Knowledge Discovery in Databases (KDD)

Knowledge Discovery in Databases (KDD) is a process of discovering useful patterns, information or knowledge from large data sets. The main goal of KDD is to transform raw data into information that can be understood and used for better decision-making. This process involves several stages, from data selection and cleaning, data transformation, data mining, to evaluation and interpretation of results.

2.2. FP-Growth Algorithm

The FP-Growth (Frequent Pattern Growth) algorithm is one of the association data mining algorithms used to find patterns that often appear (frequent itemset) in datasets [13]. FP-Growth is an improvement of the Apriori algorithm which is more efficient in processing large data and is able to find recurring patterns without the need to explicitly generate candidates [11]. FP-Growth determines frequent itemsets by means of the FP Tree structure, which is then used to identify association rules by calculating support and confidence values to find the relationship between products that consumers often buy together [14].

2.3. Association Rules

Association analysis or association rules is a technique in data mining that aims to find rules that meet the minimum support (Minsupp) and minimum confidence (Minconf) criteria. This method is used to identify relationships or correlations between elements in a dataset.

Support is one of the metrics used in association analysis to measure how often an itemset appears in a dataset. The support value is used to filter out patterns that appear with a certain frequency in the data. Support is calculated as the ratio of the number of transactions containing a particular itemset to the total number of transactions in the dataset. The formula for calculating support can be seen in below:

$$\text{Support}(X) = \frac{\text{Number of transactions containing itemset } X}{\text{Total number of transactions}}$$

Confidence is a metric used to measure the strength of an association rule by showing how much probability another itemset appears together with a known itemset. Confidence measures the strength of an association rule by indicating the probability that an itemset that appears in transactions will be followed by other itemsets. The higher the confidence value, the higher the probability of the rule occurring in the dataset. The confidence formula for association rule $A \rightarrow B$ can be seen below:

$$\text{Confidence}(A \rightarrow B) = \frac{\text{Number of transactions that contain } (A \cup B)}{\text{Number of transactions that contain } A}$$

Lift is one of the statistical metrics used to measure the strength of the relationship between two items in an association rule. This metric corrects for biases that may arise due to the very high frequency of items in the dataset, providing a clearer picture of the extent to which two items are interconnected, compared to random association. The lift between two items A and B in the association rule $A \Rightarrow B$ can be calculated by the formula:

$$\text{Lift}(A \Rightarrow B) = \frac{P(A \cap B)}{P(A) \cdot P(B)}$$

3. Results and Discussion

3.1. Results

3.1.1 Data Collection

The data used in this study is historical sales data for 9 months, starting from January to September 2024 downloaded from Toko Faizah Berkah. The data is stored in the form of an excel file called DATASET TOKO FAIZAH BERKAH with a total of 12,229 records consisting of 13 attributes, as shown in Table 1 below:

Attribute	Data Type
orderItemId	Real
Sellersku	Nominal
createTime	Date
orderNumber	Real
deliveredDate	Date
customerName	Nominal
shippingCountry	Nominal
paymentMethod	Nominal
unitPrice	Integer
itemName	Nominal
variation	Nominal
shippingProvider	Nominal
status	Nominal

3.1.2 Data Selection

The process model at the Data Selection step in RapidMiner can be seen in Figure 2

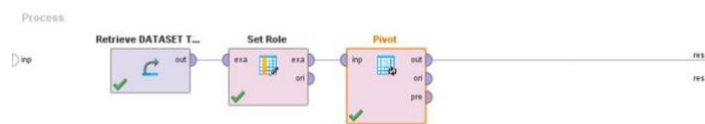


Figure 2 : Data Selection Process in RapidMiner

To import a dataset into the RapidMiner process, the Retrieve operator is used. This operator serves to retrieve the dataset stored in the local repository and enter it into the RapidMiner process.

In the Retrieve operator there are parameters as in Table 2

Parameter	Value
Repository Entry	Dataset Penjualan Toko Faizah Berkah

The next step is to assign roles or roles in the dataset using the Set Role operator. This step aims to ensure that each attribute has the appropriate function in the analysis process. At this stage, the orderNumber attribute is set as the transaction ID using the Set Role operator. The parameters used in the Set Role operator are as in Table 3 below:

Parameter	Value
Attribute Name	orderNumber
Target Role	ID

From the reading results of the Set Role operator, the following information is obtained.

No.	Name	Description
1.	Record	12.229
2.	Special Attribute	1
3.	Reguler Attribute	12
4.	Attribute :	
	orderItemId	Real
	Sellersku	Nominal
	createTime	Date
	orderNumber	Real
	deliveredDate	Date
	customerName	Nominal
	shippingCountry	Nominal
	paymentMethod	Nominal
	unitPrice	Integer
	itemName	Nominal
	variation	Nominal

<i>shippingProvider</i>	<i>Nominal</i>
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The next step is to change the dataset structure by using the Pivot operator . This operator serves to transform the raw data into a format suitable for the FP-Growth algorithm. At this stage, the data that was originally arranged in a long table format (each row represents an individual item in a transaction) is converted into a wide table format, where each row represents a complete transaction along with a list of products purchased together. The parameters used in the Pivot operator are as in Table 5 below:

Table 5 : Pivot Parameters	
Parameter	Value
Group by Attributes	orderNumber
Column Grouping Attribute	sellerSku
Aggregation Attributes	
Aggregation Attribute	sellerSku
Aggregation Function	Count

Table 6 below are the results of data transformation after processing using the Pivot operator :

Table 6 : data after processing using the Pivot operator					
Row No	orderNumber	Count(sellerSku)_BABY HAPPY-S	...	Count(sellerSku)_TISU PASEO-PINK	
1	1360250282184039	?	...	?	
2	1372528901903362	?	...	?	
3	1360075081466362	?	...	?	
4	1372249381842435	?	...	?	
5	1372208789528009	?	...	?	
6	1372195359645658	?	...	?	
7	1359952240367426	?	...	?	
8	1372186547222308	?	...	?	
9	1372180533743405	?	...	?	
10	1359917284408651	?	...	?	
11	1359921650877909	?	...	?	
12	1359905602942030	?	...	?	
13	1372100778228911	?	...	?	
14	1372089150217951	?	...	?	
15	1372050761120112	?	...	?	
...	...	...	...	...	
6634	1518659825104194	?	...	?	

3.1.3 Data Pre-processing

The process model at the Pre Processing step in RapidMiner can be seen in Figure 3

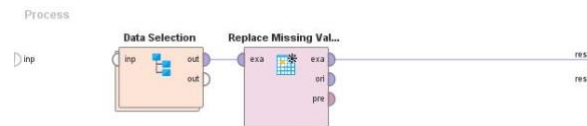


Figure 3: Pre Processing process model in RapidMiner

The data cleansing process is carried out in the preprocessing step to handle data that has missing or inconsistent values. To handle missing values, the missing values are filled using the Replace Missing Values operator in RapidMiner, by replacing the missing values in the dataset attributes with zero (0). The parameters of the Replace Missing Values operator used, as in Table 7 below:

Table 7 : Replace Missing Values Parameter	
Parameter	Value
Attribute Name	all
Default	Zero

After using the Replace Missing Value operator, all attributes in the dataset have been updated, and the missing values have been replaced with zero. Table 8 is the result of data preprocessing after being processed using the Replace Missing Value operator :

Table 8 : Data After Being Processed Using The Replace Missing Value Operator			
No	Name	Type	Missing
1	orderNumber	Real	
2	sellerSku	Nominal	
3	Count(sellerSku)_BABY HAPPY-S	Integer	0
4	Count(sellerSku)_BABY HAPPY-XL	Integer	0
5	Count(sellerSku)_BABY HAPPY-XXL	Integer	0
6	Count(sellerSku)_BABY HAPPY-L	Integer	0
7	Count(sellerSku)_BABY HAPPY-M	Integer	0
8	Count(sellerSku)_BRONZE MINI-L5	Integer	0
9	Count(sellerSku)_BRONZE MINI-M5	Integer	0
10	Count(sellerSku)_BRONZE MINI-XL4	Integer	0
..	...	...	...
129	Count(sellerSku)_TISU PASEO-PINK	Integer	0

3.1.4 Data Transformation

The process model at the Transformation step in RapidMiner can be seen in Figure 4.9 below:

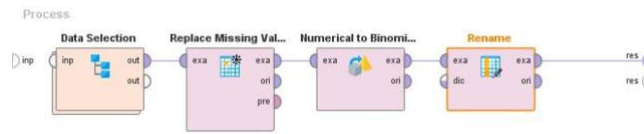


Figure 4: Transformation Process Model In Rapidminer

The next step is the transformation of numeric data attributes into binominal (binary) attributes using the Numerical to Binominal operator. This transformation needs to be done because the data type in the dataset is numeric, while the FP-Growth association algorithm requires binominal type data. This transformation is important so that the data matches the format required by the FP-Growth algorithm. The parameters of the Numerical to Binominal operator used, as in Table 9 below:

Table 9: Numerical to Binominal Parameter

Parameter	Value
Attribute Name	all
Default	Zero

Table 10 below is the result of data transformation after processing using the Numerical to Binominal operator:

Table 10 : Data After Processing Using The Numerical To Binominal Operator

Row No	orderNumber	Count(sellerSku)_BABY HAPPY-S	...	Count(sellerSku)_TISU PASEO-PINK
1	1360250282184039	false	...	false
2	1372528901903362	false	...	false
3	1360075081466362	false	...	false
4	1372249381842435	false	...	false
5	1372208789528009	false	...	false
6	1372195359645658	false	...	false
7	1359952240367426	false	...	false
8	1372186547222308	false	...	false
9	1372180533743405	false	...	false
10	1359917284408651	false	...	false
11	1359921650877909	false	...	false
12	1359905602942030	false	...	false
13	1372100778228911	false	...	false
14	1372089150217951	false	...	false
15	1372050761120112	false	...	false
...	...	...	...	...
6634	1518659825104194	false		false

The next step is to rename or update the attribute names in the dataset using the Rename operator. This operator is used to make the attribute names more descriptive and easy to understand during the analysis process. In this research, the attributes used are the columns from the previous transformation.

The parameters used in the Rename operator can be seen in Table 11 below:

Table 11 : Rename Parameters

No	Parameter	Nilai	
		oldNames	newNames
	Rename Attributes	Edit List....	
1	count(sellerSku)_6 PCS MINISSET	6 PCS MINISSET	
2	count(sellerSku)_BABY HAPPY-S	BABY HAPPY-S	
3	count(sellerSku)_BABY HAPPY-XL	BABY HAPPY-XL	
4	count(sellerSku)_BABY HAPPY-XXL	BABY HAPPY-XXL	
5	count(sellerSku)_BB HAPPY- L	BB HAPPY- L	
6	count(sellerSku)_BB HAPPY-M	BB HAPPY-M	
7	count(sellerSku)_BRONZE MINI-L5	BRONZE MINI-L5	
8	count(sellerSku)_BRONZE MINI-M5	BRONZE MINI-M5	
9	count(sellerSku)_BRONZE MINI-XL4	BRONZE MINI-XL4	
10	count(sellerSku)_BRONZE UNYIL -L5	BRONZE UNYIL -L5	

...	...	...	...
128	count(sellerSku)_TISU PASEO- PINK	TISU PASEO- PINK	

3.1.5 Data Mining

Next, the FP-Growth algorithm is applied to determine the association between products in the dataset. The implementation process of this algorithm is done using the FP-Growth operator in RapidMiner. This operator efficiently calculates all sets of frequently occurring items in the ExampleSet, using the FP-tree data structure.

The parameters used in the FP-Growth operator.

At this stage, the parameters used in the FP-Growth operator can be seen in Table 12 below:

Table 12 : FP-Growth Parameters	
Parameter	Value
Input format	Items in dummy coded columns
Min requirement	Support
Min support	0.02

Table 13 shows the results of frequent itemsets found after the application of the FP-Growth algorithm for January to September.

Table 13 : Frequent Itemsets Results			
Size	Support	Item 1	Item 2
1	0.149	SENSI PEREKAT S20	
1	0.079	CONFIDENCE BAG- L7	
1	0.070	CONFIDENCE BAG- M8	
1	0.057	SWEAT BRONZE PANTS MINI M5	
1	0.052	SWEAT BRONZE PANTS MINI L5	
1	0.043	BRONZE UNYIL-M5	
1	0.041	GOON MINI PACK-L7	
1	0.038	CONFIDENCE BAG- XL6	
1	0.030	SWEAT BRONZE PANTS MINI XL	
1	0.024	HK PINK-XL	
1	0.018	MINYAK TELON MY BABY 150ML	
1	0.018	SENSI PEREKAT M20	
1	0.017	GOON MINI PACK-M8	
1	0.015	SENSI PEREKAT-NB12	
1	0.015	BRONZE UNYIL -L5	
1	0.013	MIXUE-XL	
1	0.013	BB HAPPY- L	
1	0.013	MIXUE FANTA -XL	
1	0.013	BABY HAPPY-S	
1	0.013	BRONZE UNYIL -XL4	
1	0.012	SABUN MYBABY REFIL-KUNING	
1	0.012	TELON MYBABY KUNING-90ML	
1	0.012	SWEETY SLVER-S	
1	0.011	BB HAPPY-M	
1	0.011	HK PINK-XXL	
1	0.010	HK PINK-L	
1	0.009	MIXUE-XXL	
1	0.009	HK PINK-M	
1	0.009	KUDAPONY-XL	
1	0.009	TELON MYBABY KUNING-150ML	
1	0.008	GOON MINI PACK-XL6	
1	0.008	K.PONY PELANGI-XL	
1	0.008	MAMYPOKO-L	
1	0.008	MIXUE-L	
1	0.007	MIXUE-M	
1	0.007	SABUN MYBABY REFIL-PINK	
1	0.006	K.PONY PELANGI-XXL	
1	0.006	MAMYPOKO-M	
1	0.005	MIXUE FANTA -L	
1	0.005	KUDAPONY-XXL	
1	0.005	KUDAPONY-L	
1	0.005	SWEETY SLVER-M	
1	0.004	MUKENAH ANAK XL	
1	0.004	P. CONFIDENCE- L	
1	0.004	BABY HAPPY-XL	
2	0.004	SWEAT BRONZE PANTS MINI M5	SWEAT BRONZE PANTS MINI L5

process is done using the Association Rules operator in RapidMiner.

The parameters used in the Association Rules operator can be seen in Table 14 below:

Table 14 : Association Rules Parameters

Parameter	Value
Criterion	Confidence
Min Confidence	0.05

Table 15 shows the results of the association rules generated by the Association Rules operator for all months.

Table 15 : Association Rules Results

No	Premises	Conclusion	Support	Confidence	Lift
1	SWEAT BRONZE PANTS MINI M5	SWEAT BRONZE PANTS MINI L5	0.004	0.073	1.421

Figure 5 is the design of the entire research process, starting from data preprocessing to the formation of association rules using the FP-Growth algorithm and Association Rules.



Figure 5: Design of the entire research process

3.1.6 Interpretation and Evaluation

a. Interpretation of Frequent Itemsets

Frequent itemsets found in this study reflect product combinations that often appear together in transactions. Based on the results presented in Table 4.15, there are a number of items that have significant support values, including the SENSI PEREKAT S20 product with a support value of 0.149, and the CONFIDENCE BAG- L7 product which has a support value of 0.079. These products with high support values indicate that they are often purchased together by customers.

b. Interpretation of Association Rules

Based on the results obtained from the Association Rules operator in Table 4.17, it can be seen that there is a fairly strong association rule between certain products. This rule indicates that if customers buy SWEAT BRONZE PANTS MINI M5, they will The next step is the formation of association rules based on the frequent itemsets generated by the FP-Growth algorithm. This most likely also buy SWEAT BRONZE PANTS MINI L5. With a support value of 0.004, this rule indicates that these two products are often purchased together in transactions. The relatively low confidence value (0.073) indicates that although there is a relationship between these two products, the relationship does not always occur in every transaction. However, a lift value greater than 1 (i.e. 1.421) indicates that the relationship between these two products is stronger than a random relationship, meaning that this combination of products is more likely to co-occur than randomly expected.

A lift greater than 1 (1.026) also indicates that the rule is reliable, though not perfect, in predicting the relationship between products. The values of support, confidence, and lift provide a more in-depth picture of the strength of association between different products and allow researchers to assess how significant the rules are in the context of the dataset used

c. Evaluation of Data Mining Results

The evaluation of the results of the FP-Growth and Association Rules is carried out based on three main aspect

1. **Support:** A higher support value indicates that the item or rule occurs more frequently in the dataset. However, products with low support are still important to consider as they may reflect the existence of a specific market segment even though their transaction volume is not as large as products with high support.
2. **Confidence:** The confidence value describes the probability of a conclusion occurring if the premises are met. In this case, even though there are association rules with low confidence, the results found still provide useful information about potential relationships between products that can be explored further.
3. **Lift:** A lift value greater than 1 indicates that the association between the products is stronger than a random association, indicating a significant relationship that can be utilized for marketing strategies. Rules with higher lifts should be prioritized as they indicate stronger linkages between products.

3.2 Discussion

The first aim of this research is to get the support and confidence values for association in sales data. Based on the results found, the FP-Growth algorithm successfully identifies associations at a parameter value of support 0.02 and confidence 0.5. With a min support value of 0.02, only product combinations that appear in at least 2% of the total transactions are considered as relevant associations. Meanwhile, a min confidence of 0.5 ensures that only associations that have a 50% or more chance of occurring are taken as valid rules. In line with research conducted by [15] in their journal entitled "Implementation of Data Mining in Data Growth Settings" states that the use of

appropriate support and confidence parameters is very important in identifying strong associations in sales data. In their research, they used min support of 0.2 and min confidence of 0.7, and found that these parameters are effective in identifying product combinations that are often purchased together.

The second aim of this research is to calculate and analyze the support, confidence, and lift values of the association rules found, which are used to assess the strength of the relationship between products found through the FP-Growth algorithm. Based on the result, an association was found between the products “SWEAT BRONZE PANTS MINI M5” and “SWEAT BRONZE PANTS MINI L5”. These values provide insight into how strong and significant the relationship is between the products in the analyzed dataset. The support value of 0.004 indicates that the association between the two products occurs in 0.4% of all transactions, which suggests that this relationship is rare but there is still a possibility of a relevant association although it is not very common. This may indicate that the products are more commonly purchased by certain market segments or under special transaction conditions.

The confidence value of 0.073 indicates that 7.3% of the transactions that contain “SWEAT BRONZE PANTS MINI M5” also contain “SWEAT BRONZE PANTS MINI L5”. With relatively low confidence, although there is a relationship between the two products, this relationship is not very strong, only a small proportion of transactions that bought “SWEAT BRONZE PANTS MINI M5” also bought “SWEAT BRONZE PANTS MINI L5”. However, this could still indicate the potential to increase sales of both products together, especially in a marketing or bundling strategy.

A lift value of 1.421 indicates that the association between the two products occurs 1.421 times more often than would be expected if the two products were randomly distributed in the transaction. A lift value greater than 1 indicates that there is a significant positive association between the two products, and with a lift of 1.421, it indicates that purchasing “SWEAT BRONZE PANTS MINI M5” increases the likelihood of purchasing “SWEAT BRONZE PANTS MINI L5”. This gives a strong signal that the two products have the potential to be sold together or in a more targeted bundling.

The third objective of this research is to identify products or items that have the highest support value in frequent itemsets. Support measures the frequency of occurrence of an item or combination of items in all transactions analyzed. The higher the support value, the more often the item appears in the transaction and the more significant the association between the items. Based on the results shown in Table 4.15, the product with the highest support value in frequent itemsets is “SENSI PEREKAT S20”, with a support value of 0.149. This relatively high support value indicates that this product appears together in a significant number of transactions. In comparison, other products such as “CONFIDENCE BAG- L7” and “CONFIDENCE BAG- M8” have a support of 0.079 and 0.070 respectively, which indicates that they also frequently appear in transactions, albeit with a lower frequency than “SENSI PEREKAT S20”.

The study conducted by [16], mentioned that products with the highest support values, such as products that are often involved in joint purchases, should be the focus of promotion planning and product bundling. Their findings support the importance of analyzing products with high support values for more effective marketing strategies, as found in this study for SENSI PEREKAT S20 products. These high-support products have the potential to significantly increase sales if positioned well in the right offer or promotion.

4. Conclusions

From the results of the research conducted, several important conclusions were obtained that can be the basis for understanding consumer purchasing patterns and developing product management strategies. The following are the conclusions of this research:

1. Based on the research conducted, the min support parameter value used to find associations in sales data is 0.02 (2% of total transactions), while the min confidence value required is 0.5 (50% probability of association). With these values, the FP-Growth algorithm successfully identifies relevant associations in the sales data.
2. Based on the analysis of association rules, a relationship was found between the products SWEAT BRONZE PANTS MINI M5 and SWEAT BRONZE PANTS MINI L5, with a support value of 0.004, confidence of 0.073, and lift of 1.421. The low support value indicates that this rule is rare in the dataset, but the low confidence and lift greater than 1, respectively, indicate that although the relationship between the two products is not very frequent, the relationship is stronger than a random relationship and may provide opportunities for marketing strategies, such as product bundling.
3. The product “Sensi Adhesive S20” has the highest support value of 0.149 (14.9%), making it a product with significant appeal among consumers. This high support value indicates that the product is one of the most frequently purchased items, so it has great potential to be a key focus in inventory management strategies.

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