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Identify Rattan Sales Patterns Using the FP-Growth Algorithm on CV. Busaeri Rattan

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Abstract

This research was conducted to recognize the pattern of purchasing rattan products at CV. Busaeri Rattan by utilizing the FP-Growth algorithm. The rattan industry is faced with the challenge of understanding consumer habits in order to improve marketing strategies. The FP-Growth algorithm was chosen for its ability to efficiently identify frequent itemset patterns without requiring a lot of memory. This research includes collecting rattan sales transaction data for one year, data preprocessing, FP-Tree structure formation, and frequent itemset analysis. The analysis was conducted using RapidMiner software with a minimum support setting of 0.005 and confidence of 0.1. The processed data was then used to find combinations of products that are often purchased together. The results revealed some significant patterns, such as the products "Mandola 3/4" and "Jawit 8/11," which are often purchased together with a confidence level of 100%. These findings provide important insights for CV. Busaeri Rattan in increasing sales through promotional strategies such as bundling or discount offers. In addition, the FP-Growth algorithm proved to be faster and more resource-efficient than traditional methods such as Apriori. The discussion shows that the discovered purchasing patterns can help CV. Busaeri Rattan better manage stock, minimize the risk of running out of goods, and design data-driven marketing strategies. The combination of products that are often purchased together can be utilized to improve customer satisfaction as well as operational efficiency. The conclusion of this research is that the FP-Growth algorithm is an effective tool for analyzing large-scale transaction data. Further research is recommended to explore the application of this algorithm to other types of products or compare it with other data mining algorithms.

Keywords: *FP-Growth, Data Mining, Sales Patterns*

1. Introduction

Rapid developments in the field of information technology have had a significant impact in various sectors, including business and commerce. Information technology enables more in-depth data analysis to understand consumer behavior and develop data-driven marketing strategies. In the rattan industry, one of the leading sectors in Indonesia, information technology can be a solution to efficiently identify consumer needs [1][2].

CV. Busaeri Rattan as a manufacturer of rattan products faces challenges in recognizing complex consumer purchasing patterns. If these patterns are not well identified, the company may experience obstacles such as poorly targeted promotions or inefficient stock management. The FP-Growth algorithm was chosen for its ability to identify frequent itemsets without requiring much memory, making it a relevant solution in analyzing sales data [3][4].

It is able to identify frequent itemsets efficiently without requiring a complex candidate search process, making it more memory-efficient than the Apriori algorithm [3][4]. In the retail sector, this algorithm has helped companies to optimize data-driven promotions, improve stock management, and understand consumer behavior [5][6].

Research on the application of the FP-Growth algorithm in the rattan industry is still limited. In fact, this sector has complex purchasing patterns and the need to understand consumer preferences to improve competitiveness. This research fills the gap by applying the FP-Growth algorithm to analyze transaction data at CV. Busaeri Rattan. The main objectives of this research are to identify rattan products that are often purchased together by consumers, provide recommendations for data-based marketing strategies that can increase sales, and develop new insights into the application of the FP-Growth algorithm in traditional sectors such as the rattan industry [7].

The results of this study are expected to not only improve the efficiency of stock management and promotion, but also contribute to the literature on the application of the FP-Growth algorithm in other categories to use data mining technology [7].

1.1. Algoritma FP-Growth

FP-Growth is one of the algorithms applied in association data mining[8]. This algorithm plays a role in recognizing frequent itemsets in a data set by setting a minimum support value. FP-Growth is an advancement of the a priori algorithm which eliminates the candidate formation stage. FP-Growth is part of the association rule method in data mining which aims to reveal the rule relationship among a group of items by considering the frequency of existing data[9].

1.2. Knowledge Discovery Database

Knowledge Discovery in Databases (KDD) is the process of identifying valid, novel, potentially useful, and understandable patterns from large datasets. It involves multiple steps, starting with data selection, preprocessing, and transformation, followed by data mining to extract patterns, and finally, interpreting and evaluating the results. KDD serves as the foundation for extracting actionable insights and knowledge from raw data, often leveraging advanced techniques such as machine learning, statistics, and data visualization to uncover hidden relationships and trends[10].

2. Research Method

2.1. Research Method

The methodology employed in this research is Knowledge Discovery in Databases (KDD). The workflow or sequence of steps utilized throughout the study is depicted in Figure 1 below.

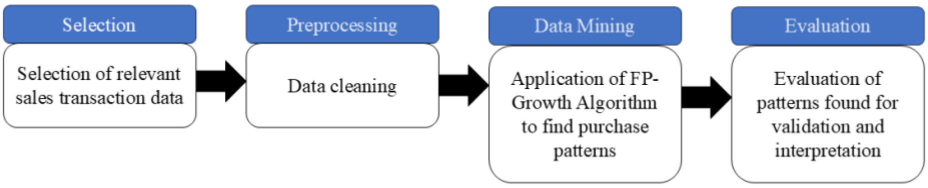

Fig. 1: Research Method

3. Result and Discussion

3.1. Selection

At this stage, relevant sales transaction data is selected from the database. This involves identifying a subset of the data to be analyzed, such as purchase date, consumer name, invoice number, item name, price, KG weight unit, Ball weight unit, and transaction amount. The goal is to ensure that the data selected reflects the problem you want to solve or the pattern you want to discover. In the initial stage of this research, the data analysis process aims to select and collect relevant data according to the research objectives. At this stage, the data to be used is identified and filtered to suit the analysis needs, as in the case of research on sales of rattan products at CV. Busaeri Rattan. With data that has been selected, we can focus more on identifying patterns to be analyzed, so that the data processing process becomes more effective and accurate.

1	Invoice	Nama Barang	Ball
2	003251	Jawit 8/11	24
3	003252	Jawit 8/11	27
4	003253	Jawit 8/11	1
5	003253	AB 22/30 Mandola 3/4	6
6	003253	AB 30/32 Mandola 3/4	2
7	003254	Kubu 4/6	14
8	003255	AB Mandola 3/4	1
9	003256	Jawit 6/8	10
10	003256	Jawit 8/11	3
11	003256	Kubu 6/8	17
12	003257	AB Tohiti 3/4	6
13	003258	AB Mandola 3/4	6
14	003259	AB Mandola 3/4	2
15	003260	Jawit 6/8	3
16	003261	Jawit 6/8	1
17	003262	AB Mandola 3/4	1
18	003263	Jawit 6/8	1
19	003264	Kubu 8/11	1
20	003264	Jawit 6/8	2
21	003265	AB Mandola 3/4	4
22	003266	Jawit 6/8	10
23	003267	Jawit 6/8	25
24	003268	AB Mandola 3/4	1
25	003269	Kubu 8/11	2

Fig. 2 :Data Selection

There are only 3 attributes that will be used in this research, namely "Invoice", "Goods Name" and "Ball" because this research will identify sales patterns where these patterns do not require other attributes that can cause errors at the association rules stage. No Atribut Tipe Invoice Integer Nama Barang Polynominal Ball Integer.

3.2. Preprocessing

In the previous stage, the data was selected manually using Microsoft Excel, so the results of the selection stage and preprocessing were carried out to prepare rattan sales transaction data at CV. Busaeri Rattan to suit analysis needs using the FP-Growth algorithm. Initial data consists of information on transaction date, consumer name, note number, item name, price, unit weight, quantity in balls, and total transaction amount. However, for the needs of association analysis, this data is processed to focus only on the note number, item name and amount in the ball. Once the data is selected, the next step is to clean the data from errors and inconsistencies. This includes filling in missing values, fixing formatting errors, and retrieving only important data. This process may also include data normalization to ensure that all entries are in a consistent format and can be used for further analysis.

4–5	NO	Tanggal	Konsumen	No Nota	Nama Barang	Harga	Satuan Berat KG	Satuan Berat Ball	Jumlah
6	1	02 Januari 2023	Sakti	003251	Jawit 8/11	11.700	1.956	24	22.885.200
7	2		Sunarsa	003252	Jawit 8/11	11.700	2.303	27	26.945.100
8	3		CV.Manunggal	003253	Jawit 8/11	13.000	77	1	1.001.000
9					AB 22/30 Mandola 3/4	19.500	460	6	8.970.000
10					AB 30/32 Mandola 3/4	19.000	144	2	2.736.000
11	4		Jaya	003254	Kubu 4/6	14.000	1.021	14	14.294.000
12	5		Cash	003255	AB Mandola 3/4	19.000	18	1	342.000
13	6		PT.Cirebon Furniture	003256	Jawit 6/8	12.500	786	10	9.825.000
14					Jawit 8/11	12.500	274	3	3.425.000
15					Kubu 6/8	11.750	1.457	17	17.119.750
16	7		Jani	003257	AB Tohiti 3/4	19.000	378	6	7.182.000
17	8		Will	003258	AB Mandola 3/4	19.000	69		1.311.000
18	9	03 Januari 2023	Uus	003259	AB Mandola 3/4	18.000	128	2	2.304.000
19	10		Warnoto	003260	Jawit 6/8	12.750	210	3	2.677.500
20	11		Cash	003261	Jawit 6/8	12.750	83	1	1.058.250
21	12		Cash	003262	AB Mandola 3/4	19.000	22		418.000
22	13	04 Januari 2023	Akrom	003263	Jawit 6/8	12.750	79	1	1.007.250
23	14		Risna	003264	Kubu 8/11	12.500	72	1	900.000
24					Jawit 6/8	12.750	152	2	1.938.000
25	15		Uus	003265	AB Mandola 3/4	18.000	336	4	6.048.000
26	16		Yoyon	003266	Jawit 6/8	13.000	673	10	8.749.000
27	17	05 Januari 2023	Sunarsa	003267	Jawit 6/8	11.700	2.147	25	25.119.900
28	18		Cash	003268	AB Mandola 3/4	19.000	14	1	266.000
29	19		Tatang	003269	Kubu 8/11	11.500	160	2	1.840.000
30	20	09 Januari 2023	PT.Indigo Mandiri Sejahtera	003270	Jawit 6/8	13.750	250	3	3.437.500
31	21		Uus	003271	AB Mandola 3/4	18.000	60	1	1.080.000
32	22		Rosyid (Cimoy)	003272	AB Mandola 3/4	19.000	141	2	2.679.000
33					BC Mandola 3/4	16.000	156	2	2.496.000
34	23		Mamat	003273	Bontongan	6.750	314	7	2.119.500
35	24		Warnoto	003274	Jawit 6/8	12.750	149	2	1.899.750
36	25		Yanto	003275	AB Tohiti 3/4	19.000	142	2	2.698.000
37	26	10 Januari 2023	Uus	003276	AB Mandola 3/4	18.000	82	1	1.476.000
38	27		Jani	003277	Jawit 6/8	12.250	1.726	20	21.143.500
39	28		Kandar	003278	AB FP Mandola	20.000	136	2	2.720.000
40	29	12 Januari 2023	PT.Cirebon Furniture	003279	Tiger	8.000	213	3	1.704.000
41	30		Risna	003280	Jawit 6/8	12.750	177	2	2.256.750

Fig. 3: Before preprocessing

At this data mining stage, data analysis is carried out using the FP-Growth algorithm method. This method was chosen to identify purchasing patterns that often occur in rattan product sales transaction data at CV. Busaeri Rattan. The FP-Growth algorithm can find combinations of products that are often purchased together. After opening Rapidminer a display will appear as in the image above. Then the next stage is the drag and drop operator which will be used in this research.

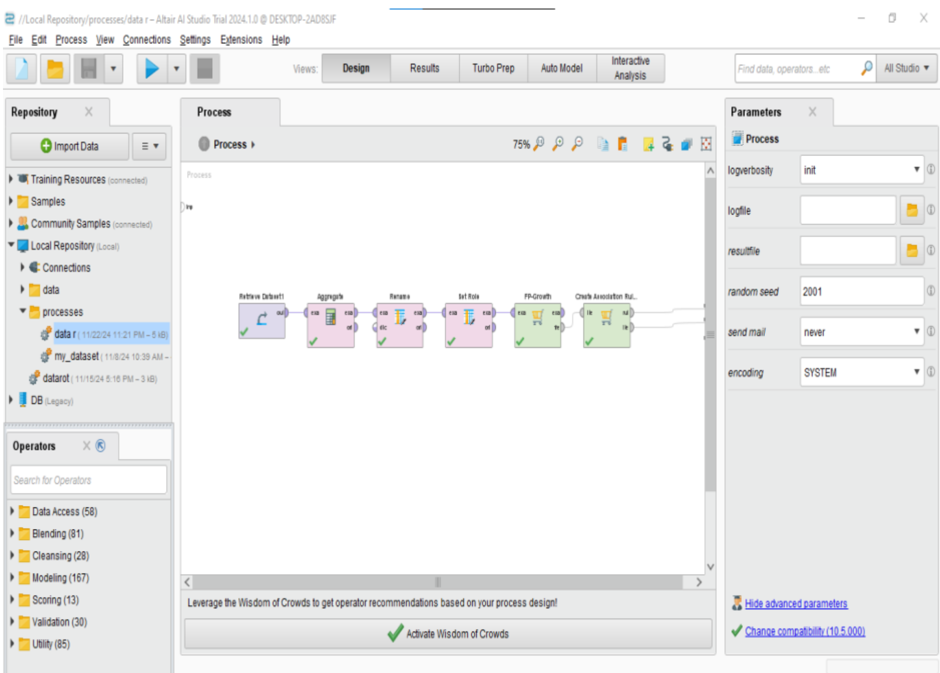

Fig. 4: Operator view

3.3. Data Mining

After a pattern is found, an evaluation stage is carried out to assess the relevance and quality of the pattern. This involves analyzing the resulting patterns to ensure that they are useful and applicable in a business context. Evaluation may also include testing patterns against new data to validate that they remain consistent and reliable. Operators used in processing CV sales data. Busaeri Rattan includes the Retrieve Dataset1, Aggregate, Rename, Set Role, FP-Growth, and Create Association Rules operators.

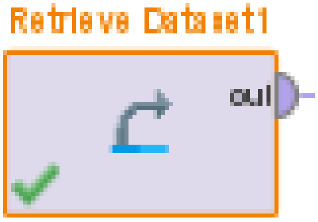

Fig. 5: Retrieve

The Retrieve Operator loads the Altair RapidMiner Object into the Process. This object is often an ExampleSet but can also be a Collection or Model. Retrieving data this way also provides meta data from the Altair RapidMiner Object.

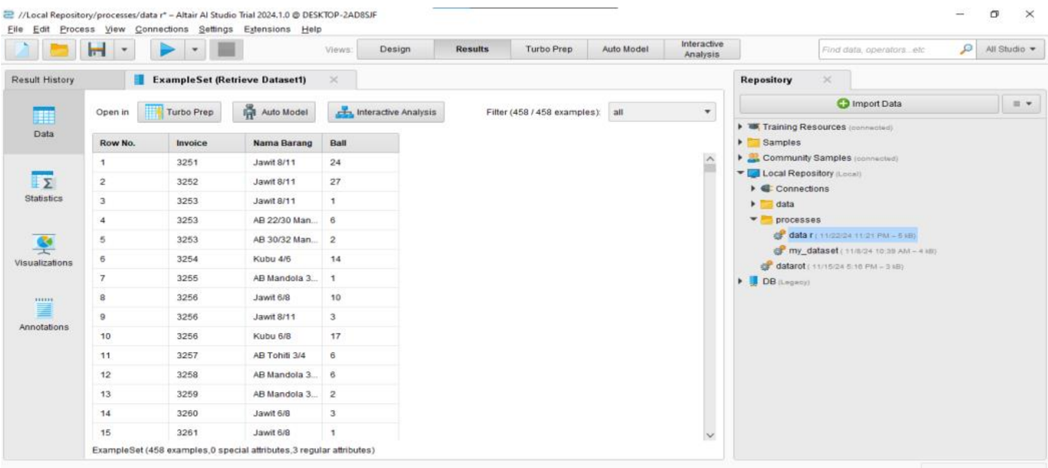

Fig. 6: After running 1

The dataset has been successfully imported into the Altair AI Studio platform with the appropriate data structure for further analysis using the FP-Growth algorithm that the dataset is correct.

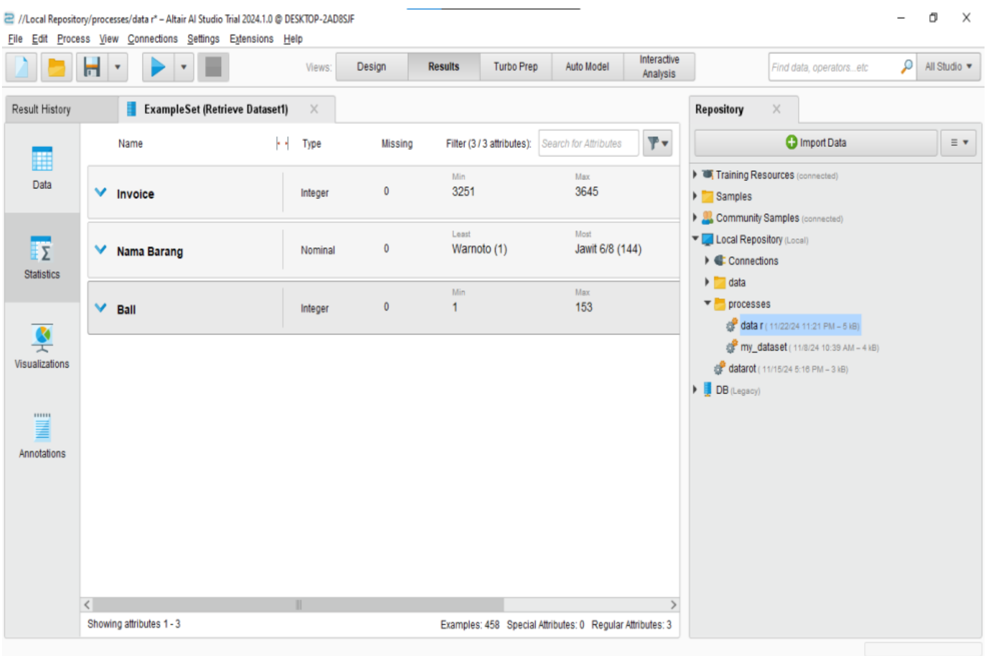

Fig. 7: After running 2

The dataset has been verified and there are no missing values in the three attributes, namely Invoice, Item Name, and Ball. The Invoice attribute is of type Integer, the Item Name attribute is of type Nominal, and the Ball attribute is of type Integer.

Fig. 8: Aggregate

Aggregate operators focus on obtaining summary information, such as averages and sums, etc. The Aggregate operator can group examples in an ExampleSet into smaller sets and apply Aggregation functions to those sets.

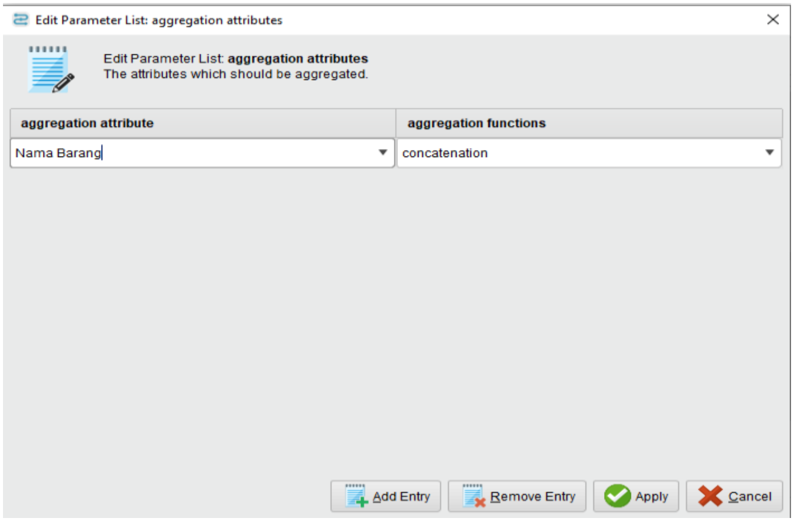

Fig. 9: Aggregate attributes

In Parameters Aggregate, click Edit List, then a display will appear as in Figure 4.10. Aggregate Attributes To change the "Item Name" variable to concatenation, in the aggregation attribute display, we look for "Item Name", then in the aggregation functions display, we look for concatenation, then click. After that, click Apply, then the "Item Name" will automatically become concatenation.

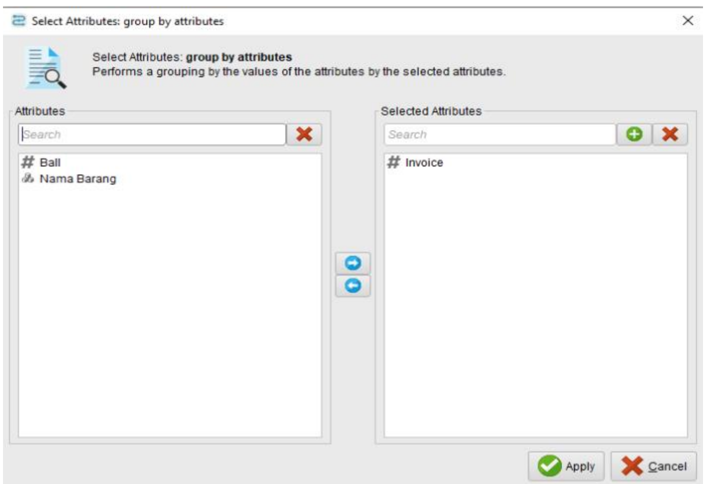

Fig. 10: Group by attributes

In Parameters Aggregate, click Edit List, then a display will appear as in Figure 4.11. Group By Attributes is a step in the process of grouping data using certain attributes as the basis for grouping (group by attributes). The Invoice attribute is selected as the basic attribute for grouping data. Other attributes, namely Ball and Item Name, will be grouped based on the same value from the Invoice. After that, the "Apply" button will apply the changes to the dataset.

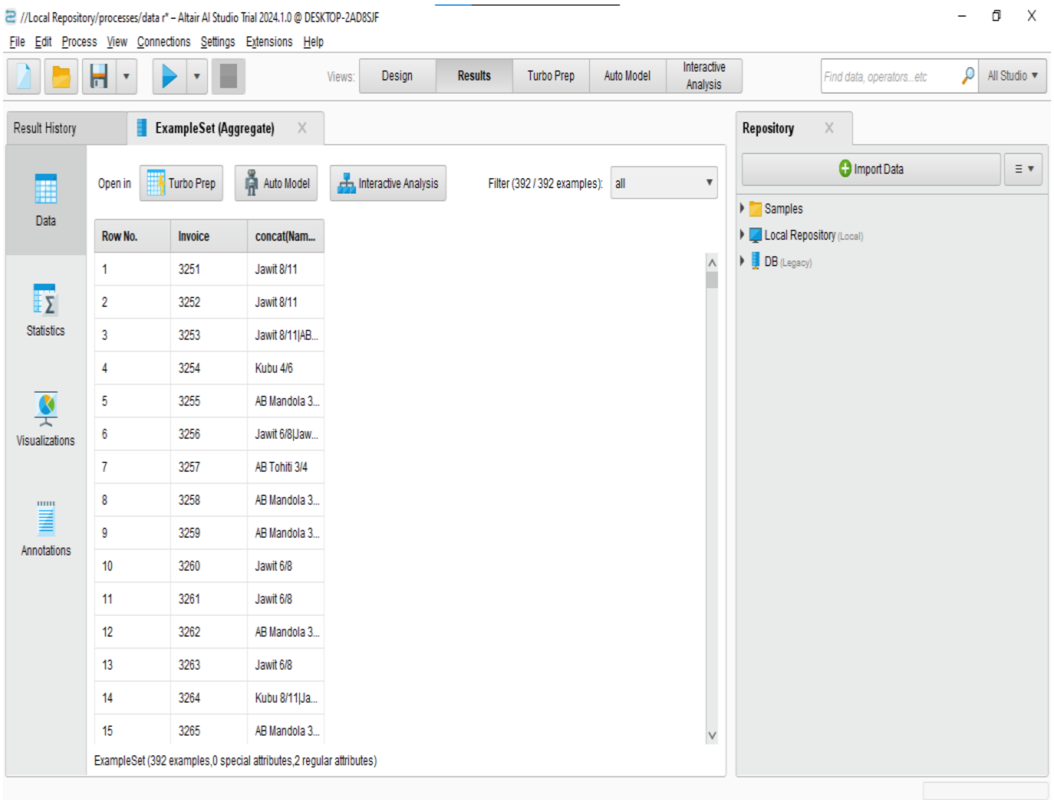

Fig. 11: Running aggregate

In Parameters Set Role, click Edit List, then a display will appear as in Figure Set Roles to change the "Invoice" variable to an ID. In the attribute name display, we look for "Invoice", then in the target role display, we look for the ID then click. After that, click Apply, then automatically "Invoice" will become an ID.

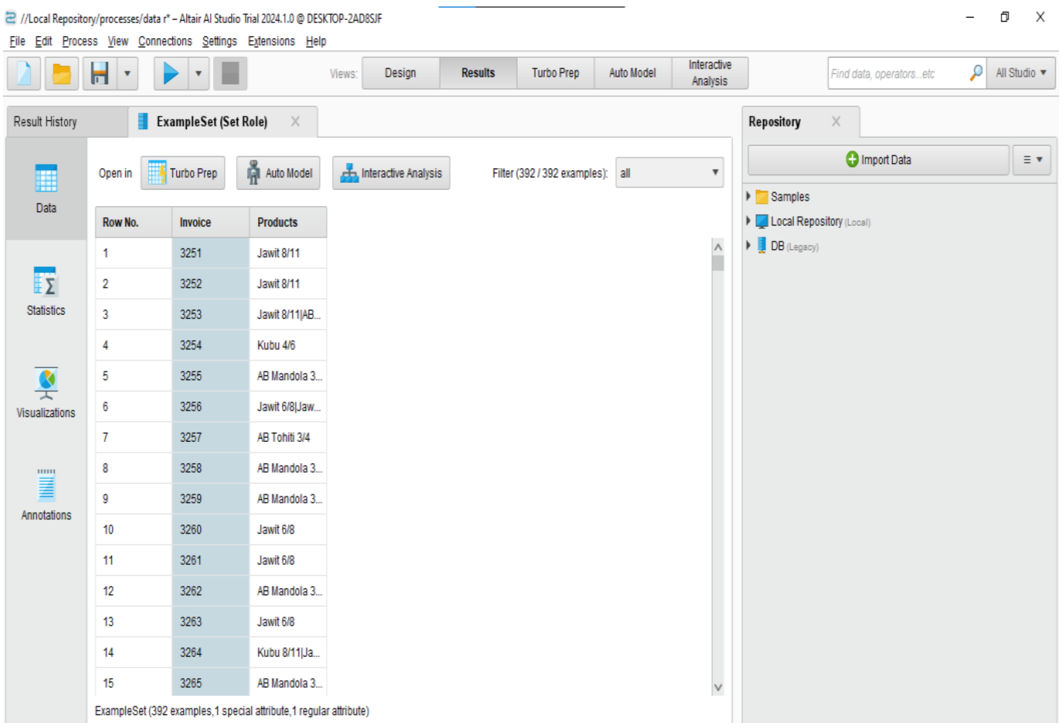

Fig. 12: Running set role

This stage carries out the Set Role process on the data that has been processed. This process results in the "Invoice" and "Products" attributes grouped based on specific roles assigned to the data. This feature allows the system to understand how the attributes mentioned above will be used in a more comprehensive analysis process, such as target or predictor attributes. With a total of 392 records, this output provides a more organized basis for subsequent data processing steps.

Fig. 13: Fp-Growth

The Fp-Growth operator is used to obtain itemsets with a high probability of occurrence (frequent itemsets) in sales data at CV.Busaeri Rattan by building FP-Tree data in the program. Then, if you want to know the number of frequent itemsets, you can do this by reducing the minimum support value in Rappidminer.

Size	Support	Item 1	Item 2	Item 3
2	0.036	Jawit 6/8	Jawit 8/11	
2	0.010	Jawit 6/8	Tiger	
2	0.008	Jawit 6/8	Jawit 4/6	
2	0.008	Jawit 6/8	Kubu 8/11	
2	0.013	Jawit 6/8	Kubu 6/8	
2	0.005	Jawit 6/8	Bontongan	
2	0.005	Jawit 8/11	Kubu 6/8	
2	0.005	Jawit 8/11	AB 22/30 Mandola ...	
2	0.005	Jawit 8/11	AB 30/32 Mandola ...	
2	0.008	AB Mandola 3/4	BC Mandola 3/4	
2	0.005	AB Mandola 3/4	Mandola Kulit	
2	0.005	P Jawit 6/8	K Jawit 4/6	
2	0.005	K Jawit 4/6	P Jawit 4/6	
2	0.005	AB 22/30 Mandola ...	AB 30/32 Mandola ...	
3	0.005	Jawit 6/8	Jawit 8/11	Kubu 6/8
3	0.005	Jawit 8/11	AB 22/30 Mandola ...	AB 30/32 Mandola ...

Fig. 14 Running Fp-Growth

In the create association rules parameters, the criterion column becomes confidence, Min confidence becomes 0.1 or 10%, Gain theta becomes 2.0, and laplace K becomes 1.0.

Premises	Conclusion	Support
Jawit 8/11	Jawit 6/8	0.036
K Jawit 4/6	P Jawit 6/8	0.005
K Jawit 4/6	P Jawit 4/6	0.005
Jawit 6/8, Kubu 6/8	Jawit 8/11	0.005
Kubu 6/8	Jawit 6/8	0.013
BC Mandola 3/4	AB Mandola 3/4	0.008
P Jawit 4/6	K Jawit 4/6	0.005
Mandola Kulit	AB Mandola 3/4	0.005
AB 22/30 Mandola 3/4	Jawit 8/11	0.005
AB 30/32 Mandola 3/4	Jawit 8/11	0.005
AB 22/30 Mandola 3/4	AB 30/32 Mandola 3/4	0.005
AB 30/32 Mandola 3/4	AB 22/30 Mandola 3/4	0.005
Jawit 8/11, Kubu 6/8	Jawit 6/8	0.005
AB 22/30 Mandola 3/4	Jawit 8/11, AB 30/32 Mandola 3/4	0.005
Jawit 8/11, AB 22/30 Mandola 3/4	AB 30/32 Mandola 3/4	0.005
AB 30/32 Mandola 3/4	Jawit 8/11, AB 22/30 Mandola 3/4	0.005

Fig. 15: Association Rules data results

The stages of data analysis results in the form of association rules obtained through the FP-Growth algorithm. This table contains a Premises column which lists the initial items or combination of items in the rule, Conclusion which shows the item or combination of items which appears as a result of the premises, and Support which describes the relative frequency of occurrence of the combination in the dataset.

3.4. Evaluation

Each rule is equipped with a Confidence value, which represents the level of confidence or probability that the conclusion will occur if the conditions (premise) are met. The results from Rapidminer are in the form of a Graph and Description.

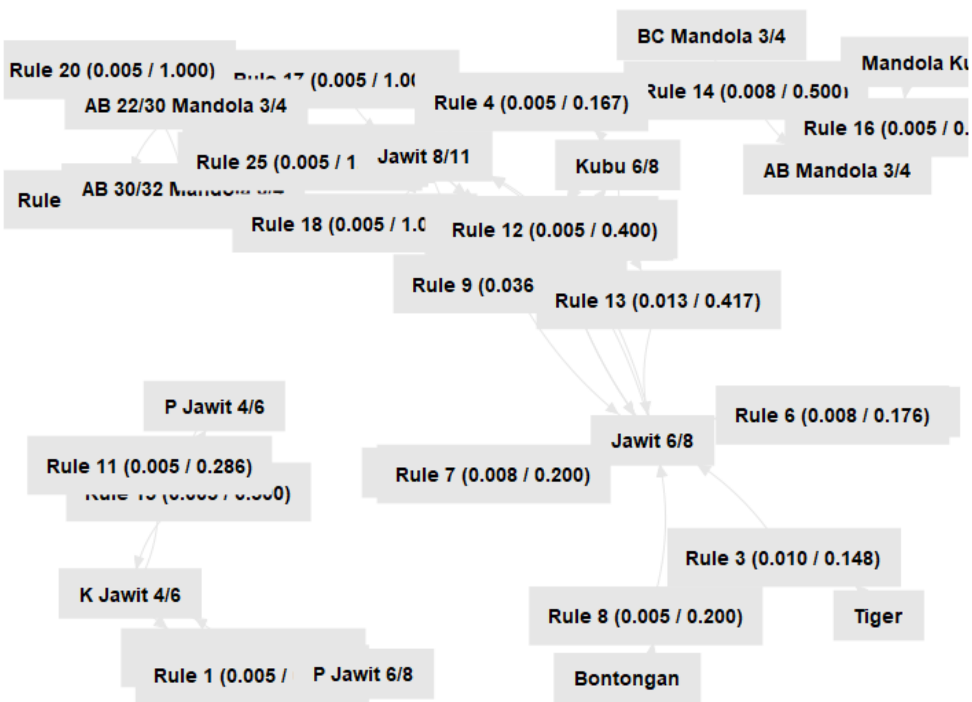

Fig. 16:Graph Association

AssociationRules

```
Association Rules
[P Jawit 6/8] --> [K Jawit 4/6] (confidence: 0.125)
[Jawit 6/8, Jawit 8/11] --> [Kubu 6/8] (confidence: 0.143)
[Tiger] --> [Jawit 6/8] (confidence: 0.148)
[Kubu 6/8] --> [Jawit 8/11] (confidence: 0.167)
[Kubu 6/8] --> [Jawit 6/8, Jawit 8/11] (confidence: 0.167)
[Jawit 4/6] --> [Jawit 6/8] (confidence: 0.176)
[Kubu 8/11] --> [Jawit 6/8] (confidence: 0.200)
[Bontongan] --> [Jawit 6/8] (confidence: 0.200)
[Jawit 8/11] --> [Jawit 6/8] (confidence: 0.215)
[K Jawit 4/6] --> [P Jawit 6/8] (confidence: 0.286)
[K Jawit 4/6] --> [P Jawit 4/6] (confidence: 0.286)
[Jawit 6/8, Kubu 6/8] --> [Jawit 8/11] (confidence: 0.400)
[Kubu 6/8] --> [Jawit 6/8] (confidence: 0.417)
[BC Mandola 3/4] --> [AB Mandola 3/4] (confidence: 0.500)
[P Jawit 4/6] --> [K Jawit 4/6] (confidence: 0.500)
[Mandola Kulit] --> [AB Mandola 3/4] (confidence: 0.667)
[AB 22/30 Mandola 3/4] --> [Jawit 8/11] (confidence: 1.000)
[AB 30/32 Mandola 3/4] --> [Jawit 8/11] (confidence: 1.000)
[AB 22/30 Mandola 3/4] --> [AB 30/32 Mandola 3/4] (confidence: 1.000)
[AB 30/32 Mandola 3/4] --> [AB 22/30 Mandola 3/4] (confidence: 1.000)
[Jawit 8/11, Kubu 6/8] --> [Jawit 6/8] (confidence: 1.000)
[AB 22/30 Mandola 3/4] --> [Jawit 8/11, AB 30/32 Mandola 3/4] (confidence: 1.000)
[Jawit 8/11, AB 22/30 Mandola 3/4] --> [AB 30/32 Mandola 3/4] (confidence: 1.000)
[AB 30/32 Mandola 3/4] --> [Jawit 8/11, AB 22/30 Mandola 3/4] (confidence: 1.000)
[Jawit 8/11, AB 30/32 Mandola 3/4] --> [AB 22/30 Mandola 3/4] (confidence: 1.000)
[AB 22/30 Mandola 3/4, AB 30/32 Mandola 3/4] --> [Jawit 8/11] (confidence: 1.000)
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Fig. 17: Association Rules Result

Shows the results of the Association Rules analysis obtained through applying the FP-Growth algorithm to rattan sales data. Association Rules describe the relationship between products that are often purchased together, with a confidence value indicating the level of confidence in this relationship. Each rule shows the probability of a customer purchasing a particular product based on other products they have purchased. The following is an explanation of each rule produced in the analysis:
a) If those who buy "P Jawit 6/8" have a 12.5% probability of buying "K Jawit 4/6."
b) If those who buy "Jawit 6/8" and "Jawit 8/11" have a 14.3% probability of buying "Kubu 6/8."
c) If those who buy "Tiger" have a 14.8% probability of buying "Jawit 6/8."
d) If those who buy "Kubu 6/8" have a 16.7% probability of buying "Jawit 8/11.
e) If those who buy "Kubu 6/8" and "Jawit 8/11" have a 16.7% probability of buying "Jawit 6/8."
f) If those who buy "Jawit 4/6" have a 17.6% probability of buying "Jawit 6/8."
g) If those who buy "Kubu 8/11" have a 20.0% probability of buying "Jawit 6/8."
h) If those who buy "Bontongan" have a 20.0% probability of buying "Jawit 6/8."
i) If those who buy "Jawit 8/11" have a 21.5% probability of buying "Jawit 6/8."
j) If you buy "K Jawit 4/6" there is a 28.6% probability of buying "P Jawit 6/8."
k) If you buy "P Jawit 6/8" there is a 28.6% probability of buying "K Jawit 4/6."
l) If those who buy "Jawit 6/8" and "Kubu 8/11" have a 40.0% probability of buying "Jawit 8/11."
m) If those who buy "Kubu 6/8" have a 41.7% probability of buying "Jawit 6/8."
n) If you buy "BC Mandola 3/4" there is a 50.0% probability of buying "AB Mandola 3/4."
o) If you buy "P Jawit 4/6" there is a 50.0% probability of buying "K Jawit 4/6."
p) If you buy "AB Mandola 3/4" there is a 66.7% probability of buying "BC Mandola 3/4."
q) If someone buys "AB 30/32 Mandola 3/4" they will definitely also buy "AB 22/30 Mandola 3/4" with a 100% confidence level.
r) If someone buys "AB 30/32 Mandola 3/4" they will definitely also buy "Mandola 3/4" with a 100% confidence level.
s) If someone buys "Mandola 3/4" they will definitely also buy "AB 30/32 Mandola 3/4" with a 100% confidence level.
t) If those who buy "Mandola 3/4" will definitely also buy "AB 22/30 Mandola 3/4" with a 100% confidence level.
u) If you buy "AB 22/30 Mandola 3/4" and "AB 30/32 Mandola 3/4" you will definitely buy "Mandola 3/4" with a 100% confidence level.
v) If those who buy "AB 22/30 Mandola 3/4" and "Mandola 3/4" will definitely buy "AB 30/32 Mandola 3/4" with a 100% confidence level.
w) If those who buy "AB 22/30 Mandola 3/4" and "Mandola 3/4" will definitely buy "AB 30/32 Mandola 3/4" with a 100% confidence level.
x) If you buy "AB 22/30 Mandola 3/4" and "AB 30/32 Mandola 3/4" you will definitely buy "Jawit 8/11" with a 100% confidence level.
Results of analysis of product purchasing patterns at CV. Busaeri Rattan provides strategic insights that can be utilized for various aspects of business. In stock management, linkage patterns between products such as Mandola 3/4 and AB 30/32 Mandola 3/4 allow companies to prioritize the availability of these products so that the risk of stock shortages can be minimized. From a marketing perspective, promotions in the form of bundling or discounts for products with strong relationships, such as Kubu 6/8 and Jawit 8/11, can be used to encourage increased sales. Apart from that, understanding product relationships also helps CV. Busaeri Rattan developed a more specific marketing strategy, such as encouraging sales of products with weak links, for example Tiger. By providing product packages that suit customers' shopping habits, companies can not only increase customer satisfaction but also build their loyalty.

4. Conclusion

Results from analysis of rattan sales data at CV. Busaeri Rattan, using the FP-Growth algorithm, has produced a number of association rules based on a minimum support value of 0.005 and minimum confidence of 0.1. These rules show relationships between products that are frequently purchased together and can be used to develop marketing and stock management strategies. The association rules found include: References Hasil aturan asosiasi 1 P Jawit 6/8 --> K Jawit 4/6 Nilai Support Nilai Confidence 0.035 0.286. In the results of association rule 1 it is known that customers who buy P Jawit 6/8 have a 28.6% probability of also buying K Jawit 4/6. Based on a support value of 3.5%, with a confidence level of 28.6%, this relationship is significant enough to be utilized in designing an integrated marketing strategy involving both goHasil aturan asosiasi 2 Jawit 6/8, Jawit 8/11 -->Kubu 6/8 Nilai Support Nilai Confidence 0.0143 0.167ods. In the results of association rule 2 it is known that customers who buy a combination of Jawit 6/8 and Jawit 8/11 have a 16.7% chance of also buying Kubu 6/8. Based on support of 1.43%, with a confidence level of 16.7%, this rule shows an opportunity to develop a combination marketing approachHasil aturan asosiasi 3 Tiger --> Jawit 6/8 Nilai Support Nilai Confidence 0.0148 0.200. In the results of association rule 5 it is known that every customer who buys AB 22/30 Mandola 3/4 must also buy AB 30/32 Mandola 3/4. The support value of 5.0% with a confidence level of 100.0% shows that this pattern appears in a small number of transactions, but this strong link can be used to design an integrated sales strategy for these two goods.

The difference between the author's research and previous research lies in the sector analyzed and the type of product that is the object of study. This research applies the FP-Growth algorithm to analyze purchasing patterns of rattan craft products at CV. Busaeri Rattan, related to previous research such as that conducted by (Anwar et al., 2023) and (Hartanti & Atina, 2023), focuses more on the e-commerce and supermarket sectors, with more general products such as fashion or food and drinks, which has a larger and more dynamic market. This research uses the FP-Growth algorithm to find frequent purchasing patterns. The type of product analyzed is significantly different from rattan products which are more segmented and have smaller market characteristics. Apart from that, studies such as (Ismarmiaty & Rismayati, 2023) and (Saputra et al., 2023) which also use FP-Growth, focus more on fashion and electronic products, which have more varied and higher demand compared to rattan crafts. Rattan products require a more specific and focused marketing strategy. Your research provides a new approach by analyzing purchasing patterns of rattan craft products, which can be used to design more segmented marketing strategies and more efficient stock management, in contrast to research that focuses on products with greater and more general demand.

Furthermore, (Nurmayanti et al., 2021) and (Supinah et al., 2022) also used FP-Growth to analyze purchasing patterns for general retail and e-commerce products, but with a focus on daily necessities products. In contrast, the author's research focuses more on rattan craft products, which have a more limited market and tend to be xxinfluenced by seasonal factors or certain trends. Therefore, the findings from the author's research are very relevant for developing a more focused and specific marketing strategy.

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