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Implementation of Apriori and Fp-Growth Algorithms on Car Dealer Parts Sales with Association Rules

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Abstract: Data mining is the process of discovering interesting and useful patterns and relationships in large volumes of data to produce valuable information. This information can help company leaders make decisions in various business areas. Company leaders can then develop strategies to face competition in the business world, one of which is the business of selling car parts. The availability of information systems related to car parts purchase transactions can be used to determine the association of parts stored in the database. The collection of transaction data can then be analyzed using the data mining process with the apriori and fp-growth algorithms using RapidMiner, which will produce information about a set of spare parts that are always purchased together more accurately, easily, and quickly. Using the information generated, management can use this information as one of the inputs in making strategic decisions in facing business competition, such as strategies for promotional needs, buyer segmentation, inventory stock, spare parts placement, or observing customer shopping patterns.

Keywords: Association rules, Data mining, Spare parts, Apriori algorithm, Fp-growth algorithm.

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Introduction

Car sales growth in the first quarter of 2019, based on data released by GAIKINDO (Indonesian Automotive Industry Association), showed a decline. The car sales data, as shown in Table 1, recorded a 13.1% decline in car sales from manufacturers to dealers (wholesales) compared to the same quarter in 2018. Total sales in 2019 amounted to 253,863 units. Meanwhile, in 2018, 292,031 units were sold. This figure indicates that sales from manufacturers to car dealers decreased by 38,168 units.

Original Article

Table 1. Car Sales List First Quarter of 2019

No	Brand	Month			Sales	Share
		Jan	Feb	Mar	2019	%
1	TOYOTA	25.092	23.449	28.725	77.266	30
2	DAIHATSU	14.769	16.305	19.625	50.699	20
3	MITSUBISHI MOTORS	11.712	10.704	12.164	35.580	14
4	HONDA	10.064	10.637	8.144	28.845	11
5	SUZUKI	8.217	8.307	6.291	22.869	9
6	MITSUBISHI FUSO	4.671	3.916	2.957	11.544	5
7	HINO	2.756	2.723	2.670	8.149	3
8	ISUZU	2.343	1.805	1.812	5.960	2
9	WULING	360	1.199	1.194	2.753	1
10	NISSAN	387	343	3.172	3.902	2
11	DATSUN	258	632	674	1.564	1
12	MAZDA	428	429	434	1.291	1
13	DFSK	103	156	172	431	0
14	UD TRUCKS	180	250	231	661	0
15	B M W	175	175	200	550	0
16	CHEVROLET	113	179	217	509	0
17	LEXUS	-	147	192	339	0
18	HYUNDAI	88	104	81	273	0
19	TATA	99	74	66	239	0
20	SCANIA	41	55	52	148	0
21	MINI	35	40	50	125	0
22	FAW	16	10	16	42	0
23	VOLKSWAGEN	15	31	27	73	0
24	PEUGEOT	-	9	14	23	0
25	RENAULT (PC)	3	1	2	6	0
26	MAN TRUCK	8	3	3	14	0
27	AUDI	3	1	4	8	0
28	INFINITI	-	-	-	-	-
29	PROTON	-	-	-	-	-
30	HYUNDAI KOMERSIAL	-	-	-	-	-
	GRAND TOTAL	81.684	81.684	90.189	253.863	100%
	CUMULATIVE	163.674	163.674	253.863		

Source: Processed by researchers (2025)

The impact of the decline in car sales will affect spare parts sales. Given these conditions, managers must be able to make breakthroughs in marketing their products so that sales can increase. One element of a marketing strategy is promotion (Rizky et al., 2021). Promotion is an activity carried out in an effort to offer goods or services to customers so that they will buy those goods (Kharomiyah et al., 2024).

For this reason, a system is needed that can support managers in making important decisions. One such system would be one that can identify the most frequently sold spare parts, enabling managers to decide on spare part inventory for the next period (Yakub & Syahfitriani, 2020). In addition, the system could also be used to consider promotions by creating spare part sales combinations based on customer needs (Zhang, 2025) (Hidayat et al., 2021).

The objectives of this study are as follows:

1. Extracting information from spare parts sales data using data mining to assist managers in making strategic business decisions.
2. Understanding the apriori algorithm process and the fp-growth algorithm process in car spare parts sales.
3. Displaying the correlation between spare parts that are frequently purchased by customers to identify interrelated associations.
4. Applying data mining with the apriori algorithm and the fp-growth algorithm to optimize auto parts sales.

Data mining

According to (Alhillah et al., 2023), also known as Knowledge Discovery in Database (KDD) in computer science, is the process of discovering interesting and useful patterns and relationships in large volumes of data. Data mining is also supported by other fields of science such as pattern recognition, image databases, neural networks, signal processing, and spatial data analysis (Abidin et al., 2022) (Vidiya & Testiana, 2023). The stages involved in the data mining process begin with data selection from the source data to the target data, followed by preprocessing to improve data quality , transformation, data mining, and interpretation and evaluation stages that produce output in the form of new knowledge that is expected to provide better contributions. This is explained in detail as follows (Essalmi & El Affar, 2025):

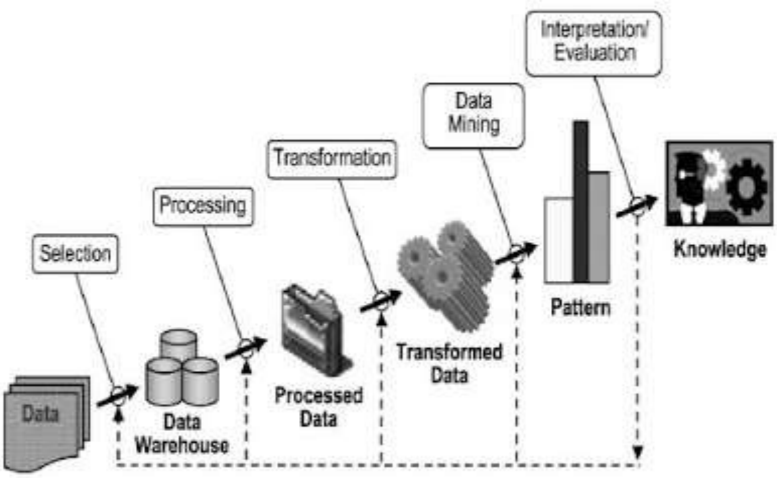


Figure 1. Data mining stages

Association Rule

In determining an association rule, there is a measure of interest obtained from the results of data management using specific calculations. According to (Erdem Günay & Yıldırım, 2021) (Wadanur & Sari, 2022), there are two measures, namely:

1. Support

   Support is a measure that indicates the frequency of an itemset's occurrence in all transactions.

2. Confidence

   Confidence is a measure that indicates the strength of the conditional relationship between two or more items.

The association rule search process is divided into two stages, namely frequent itemset analysis and association rule formation (Agrawal & Srikant, 1994).

1. Frequent Item Analysis

   Search for item combinations that meet the minimum support value in the database. The formula is as follows:

$$\text{Support (A)} = \frac{\Sigma\, Transactions\ Containing\ A}{Total\ transactions}\, x\ 100\%$$

   Meanwhile, the formula for the support value in two items is:

$$\text{Support (A. B)} = \frac{\Sigma\, Transactions\ Containing\ A\ and\ B}{Total\ transactions}\, x\ 100\%$$

2. Formulation of association rules

   Once all high-frequency patterns have been found, the next step is to search for association rules that meet the minimum confidence requirement by calculating confidence using the following formula:

$$\text{Confidence} = \text{P (BIA)} = \frac{\Sigma\, Transactions\ Containing\ A\ and\ B}{\Sigma\, Transactions\ Containing\ A}\, x\ 100\%$$

Apriori Algorithm

According to (Saputra & Fauzi, 2023), the apriori algorithm is an algorithm used for mining frequent itemsets using boolean association rules. (Iriondo Pascual et al., 2022) state that from IBM Almaden Research Center developed an association rule generation algorithm called Apriori in 1993. The definition of frequent itemset here is a set of items that meet the minimum support. Furthermore, frequent itemsets are used to build association rules (Utama et al., 2020).

The general working principle of the Apriori algorithm is as follows:

1. Formation of candidate k-itemsets from combinations of (k-1) itemsets obtained from previous iterations. Then, k-itemsets whose subsets contain k-1 items are pruned, excluding those with a length of k-1 in the high-frequency patterns.
2. The support value of each candidate k-itemset is calculated by counting the number of transactions that contain all items in the candidate k-itemset. A characteristic of the Apriori algorithm is that it requires scanning the entire database for the longest k-itemsets.
3. High-frequency patterns are then determined. High-frequency patterns containing k-itemsets are determined from candidate k-itemsets that have a support value greater than the minimum support.
4. If no new high-frequency patterns are found, the entire process is stopped. If new patterns are still found, k is increased by one and the process is repeated from step 1.

FP-Growth Algorithm

According to (Hunyadi et al., 2025), FP-Growth is one alternative that can be used to determine the most frequently occurring data sets in a data set, commonly referred to as frequent itemsets.

According to Samuel (2008), the construction of an FP-tree in the FP-Growth algorithm involves the following three steps:

1. The conditional pattern base generation stage, which is a subdatabase containing prefixes and suffixes.
2. The conditional fp-tree generation stage, in which the support value of each item for the conditional pattern base is summed, and then each item that has a support value greater than or equal to the minimum support will be generated with a conditional fp-tree.
3. The frequent itemset search stage, in which if the conditional fp-tree is a single path, the frequent itemset is obtained.

Methods

In conducting this research, the author followed established rules and methods so that the research could be carried out in a gradual and consistent manner (Liu et al., 2021). The following is an overview of the steps involved in conducting this research:

1. Identifying Problems

   Identify problems and determine their limitations in advance, with the aim of finding solutions and determining the objectives and benefits to be achieved.
2. Analyzing Problems

   Analyzing problems is a step to understand the scope or limitations of the problem with the hope that the problem can be understood properly.
3. Data Collection

   This stage is carried out with the aim of finding out and obtaining data or information that can support this research.
4. Data Processing

   This research processes data based on the KDD (knowledge discovery in database) process.
5. Performing Analysis

   How the data mining analysis process with the apriori and fp-growth algorithms is designed based on the collected data, then how to develop the data mining analysis process with association rules and the apriori and fp-growth algorithms to obtain the relationship between each item.
6. Implementation

   In this study, the author implemented the results of data analysis using the FP-tree and FP-growth algorithms with the help of a computer with a Windows operating system and RapidMiner software version 9.5

Original Article

Results

The object of this study is the sales data of "XYZ Car Dealer" spare parts in 2023, which is divided into two stages, namely training data and testing data. The training data was taken from January to November 2016, while the testing data was taken in December 2019.

Data Collection

This study uses spare parts sales data from one of Honda's dealers. The amount of data used is approximately 10,922 records. Table 2 shows the sample sales data that will be used in the study for manual calculations.

Table 2. Sales Sample Data

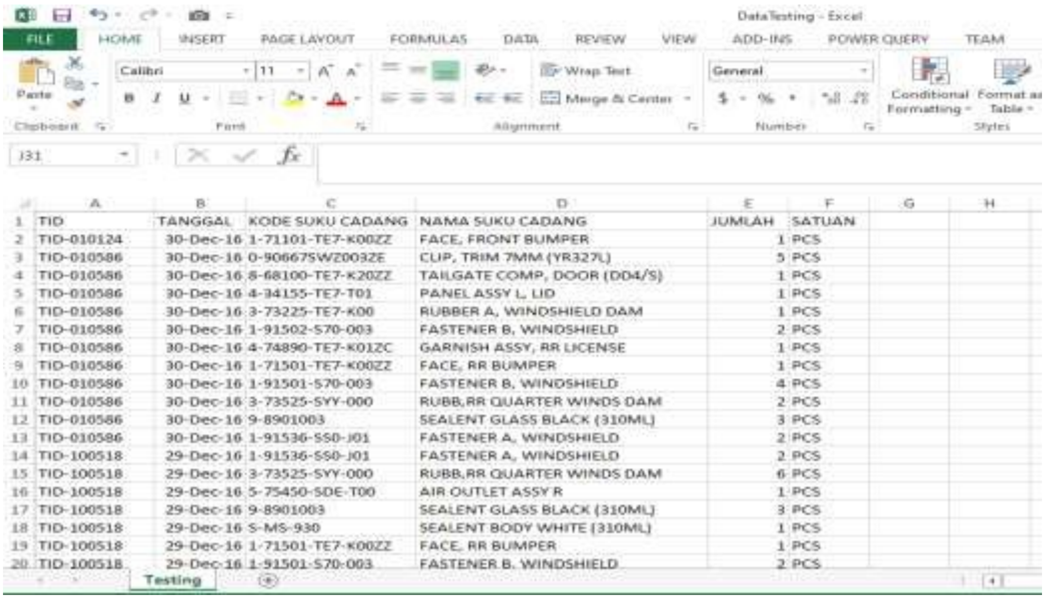
NO	TID	DATE	PARTS CODE	PARTS NAME	TOTAL	UNIT	INIT
1	TID-01	02/01/2019	4-94109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
2	TID-01	02/01/2019	8-08200-P9909ZE1	HONDA ENGINE CLEANER	1	PCS	B
3	TID-01	02/01/2019	8-08233-P99-F6NN1	HAO BLUE 5W-30 SN GF-5	1	LTR	C
4	TID-02	01/02/2019	4-94109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
5	TID-02	01/02/2019	5-15400-RK9-F01	CARTRIDGE, OIL FILTER	1	PCS	D
6	TID-03	01/02/2019	4-941109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
7	TID-04	14/03/2019	4-941109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
8	TID-04	14/03/2019	8-08233-P99-F6NN1	HAO BLUE 5W-30 SN GF-5	1	LTR	C
9	TID-04	14/03/2019	M-AM24B-ROCK	BRAKE & PAD CLEANER (250ML)	1	PCS	E
10	TID-05	17/03/2019	E-EXC-CARB	EXCHEM CARB CLEANER (220ML)	1	PCS	F
11	TID-05	17/03/2019	I-FIC-08956-3M	FUEL INJECTOR CLEANER 3M	1	PCS	J
12	TID-06	17/03/2019	4-94109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
13	TID-06	17/03/2019	5-15400-RK9-F01	CARTRIDGE, OIL FILTER	1	PCS	D
14	TID-06	17/03/2019	9-09060-EXCHEM	ENGINE FLUSH EXCHE (250ML)	1	PCS	G
15	TID-06	17/03/2019	X- EXC-CARB	EXCHEM CARB CLEANER (220ML)	1	PCS	F
16	TID-07	18/03/2019	4-941109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
17	TID-08	22/03/2019	4-941109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
18	TID-08	22/03/2019	5-15400-RK9-F01	CARTRIDGE, OIL FILTER	1	PCS	D
19	TID-08	22/03/2019	7-17220-RB6-ZOO	ELEMENT AIR FILTER (GE/B/M/DD)	1	PCS	H
20	TID-08	22/03/2019	8-08234-P99-A6NN1	HAO GOLD 0W-20 SN GF-5	4	LTR	I
21	TID-08	22/03/2019	9-09060-EXCHEM	ENGINE FLUSH EXCHEM (250ML)	1	PCS	G
22	TID-08	22/03/2019	I-FIC-08956-3M	FUEL INJECTOR CLEANER 3M	1	PCS	J
23	TID-09	23/03/2019	X- EXC-CARB	EXCHEM CARB CLEANER (220ML)	1	PCS	F
24	TID-10	26/03/2019	4-941109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A

25	TID-10	26/03/2019	5-15400-RK9-F01	CARTRIDGE, OIL FILTER	1	PCS	D
26	TID-10	26/03/2019	9-09060-EXCHEM	ENGINE FLUSH EXCHE (250ML)	1	PCS	G
27	TID-10	26/03/2019	X- EXC-CARB	EXCHEM CARB CLEANER (220ML)	1	PCS	F
28	TID-11	26/03/2019	4-941109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
29	TID-12	26/03/2019	4-941109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
30	TID-12	26/03/2019	5-15400-RK9-F01	CARTRIDGE, OIL FILTER	1	PCS	D

Source: Processed by researchers (2025)

Data Transformation

After the data is cleaned, data transformation is carried out, which is the stage of converting the data into a form suitable for processing with data mining. In this study, the data to be processed from the SQL Server 2005 Management Studio database will be converted into an .xlsx file (Microsoft Office Excel). The results of the data transformation are shown in Figure 2 below.



	A	B	C	D	E	F
1	TID	TANGGAL	KODE SUKU CADANG	NAMA SUKU CADANG	JUMLAH	SATUAN
2	TID-010124	30-Dec-16	1-71101-TE7-K00ZZ	FACE, FRONT BUMPER	1	PCS
3	TID-010586	30-Dec-16	0-90667SWZ003ZE	CLIP, TRIM 7MM (YR327L)	5	PCS
4	TID-010586	30-Dec-16	8-68100-TE7-K20ZZ	TAILGATE COMP, DOOR (DD4/S)	1	PCS
5	TID-010586	30-Dec-16	4-34155-TE7-T01	PANEL ASSY L, LID	1	PCS
6	TID-010586	30-Dec-16	3-73225-TE7-K00	RUBBER A, WINDSHIELD DAM	1	PCS
7	TID-010586	30-Dec-16	1-91502-S70-003	FASTENER B, WINDSHIELD	2	PCS
8	TID-010586	30-Dec-16	4-74890-TE7-K01ZC	GARNISH ASSY, RR LICENSE	1	PCS
9	TID-010586	30-Dec-16	1-71501-TE7-K00ZZ	FACE, RR BUMPER	1	PCS
10	TID-010586	30-Dec-16	1-91501-S70-003	FASTENER B, WINDSHIELD	4	PCS
11	TID-010586	30-Dec-16	3-73525-SYY-000	RUBB,RR QUARTER WINDS DAM	2	PCS
12	TID-010586	30-Dec-16	9-8901003	SEALENT GLASS BLACK (310ML)	3	PCS
13	TID-010586	30-Dec-16	1-91536-SS0-J01	FASTENER A, WINDSHIELD	2	PCS
14	TID-100518	29-Dec-16	1-91536-SS0-J01	FASTENER A, WINDSHIELD	2	PCS
15	TID-100518	29-Dec-16	3-73525-SYY-000	RUBB,RR QUARTER WINDS DAM	6	PCS
16	TID-100518	29-Dec-16	5-75450-SDE-T00	AIR OUTLET ASSY R	1	PCS
17	TID-100518	29-Dec-16	9-8901003	SEALENT GLASS BLACK (310ML)	3	PCS
18	TID-100518	29-Dec-16	S-MS-930	SEALENT BODY WHITE (310ML)	1	PCS
19	TID-100518	29-Dec-16	1-71501-TE7-K00ZZ	FACE, RR BUMPER	1	PCS
20	TID-100518	29-Dec-16	1-91501-S70-003	FASTENER B, WINDSHIELD	2	PCS

Figure 2. Transformation Results Data

Apriori Algorithm Process

After data transformation, the dataset is formed into the format shown in Table 3 below before being processed in Rapidminer.

Table 3. Sales itemset sample data

Transactions	0-00001-P	0-50820TG	0-50890TF	0-60100-T	0-60211-T	0-60610TE	0-80050-S	0-80291-T	0-80292-T	0-80410-T	0-90004-P
TID-010124	0	0	0	0	0	0	0	0	0	0	0
TID-010586	0	0	0	0	0	0	0	0	0	0	0
TID-100518	0	0	0	0	0	0	0	0	0	0	1
TID-101555	1	0	0	0	0	0	0	0	0	0	0
TID-110870	0	0	0	0	0	0	0	0	0	0	0
TID-111095	0	0	0	0	0	0	0	0	0	0	0

TID-111134	0	0	0	0	0	0	0	0	0	0	0
TID-111142	0	0	0	0	0	0	0	0	0	0	0
TID-111250	0	0	0	0	0	0	0	0	0	0	0
TID-111267	0	0	0	1	0	0	1	0	0	1	0
TID-111410	0	0	0	0	0	0	0	0	0	0	0
TID-111501	0	0	0	0	1	1	0	0	0	0	0

The data was then uploaded into Rapidminer to be processed as shown in Figure 3 below.

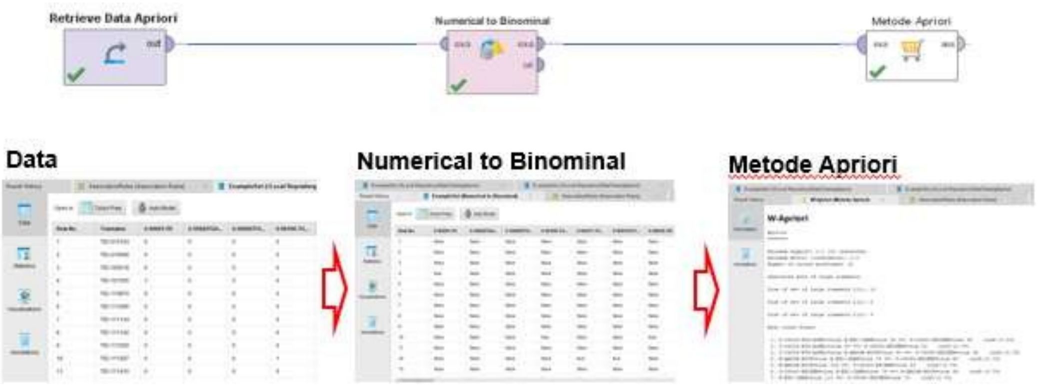


Figure 3. Apriori Algorithm Process

The data is converted into numerical to binomial and then processed using the Apriori algorithm.

FP-Growth Algorithm Process

After the data transformation is done, the data is processed in Rapidminer. The scheme is as shown in Figure 4 below.

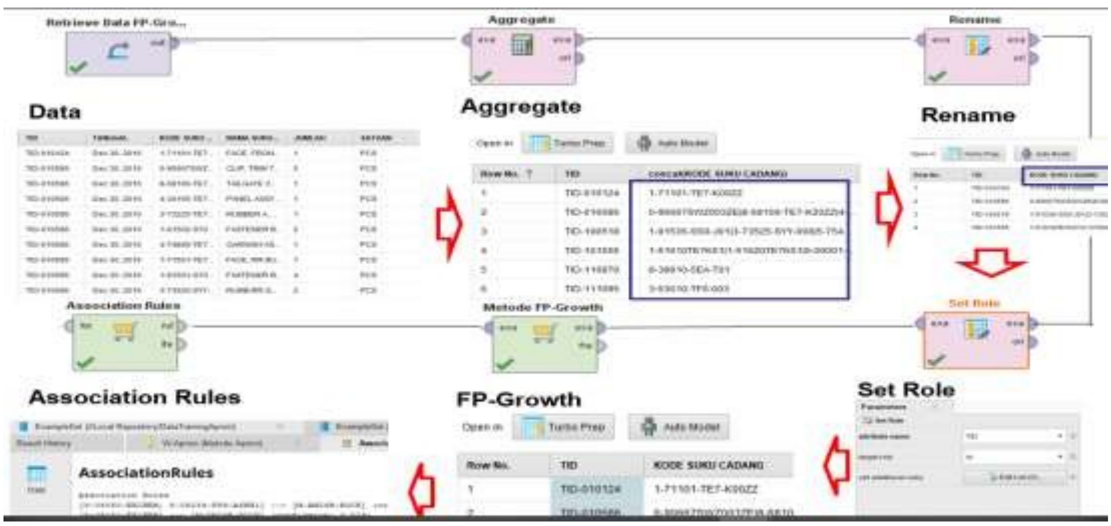


Figure 4. FP-Growth Algorithm Process

The process involves aggregating data to change its format, then renaming it to change the field name. The next process is to set roles, which aims to change the role of the attribute to be entered into the FP-Growth algorithm and processed into association rules to obtain the association rules.

Research Test Results

In conducting this research test, the support and confidence values became the basis for determining the combination patterns of associations that were entered into the test using RapidMiner. The minimum support value was set at 0.005 or 0.50%, while the minimum confidence value was set at 0.6 or 60%.

1. Training Data

The training data used was data from January to November 2016, totaling 9,851 records. Based on this data, after testing, the association rules for 2 itemsets were obtained as shown in Table 4.

Table 4. Rapidminer 2 itemset test results

No	Premises	Condusion	Confidence	
			FP-Growth	Apriori
1	8-08200-P9909ZE1	M-AM24B-ROCK	60.9%	61.0%
2	X-EXC-CARB	9-09060-EXCHEM	61.7%	62.0%
3	0-09060-EXCHEM	X-EXC-CARB	61.9%	62.0%

Meanwhile, the association rules for 3 itemsets are obtained as shown in Table 5.

Table 5. Rapidminer 3 itemset test results

No	Premises	Condusion	Confidence	
			FP-Growth	Apriori
1	M-EXC-CARB, 9-09060-EXCHEM	M-AM24B-ROCK	64.1%	64.0%
2	M-AM24B-ROCK, X-EXC-CARB	9-09060-EXCHEM	67.2%	67.0%
3	M-AM24B-ROCK, 9-09060-EXHEM	X-EXC-CARB	68.2%	68.0%

2. Data Testing

The data used for testing was data from December 2016, consisting of 1,071 records. Based on this data, after testing, the association rules for 2 itemsets were obtained as shown in Table 6.

Table 6. Rapidminer 2 itemset test results

No	Premises	Condusion	Confidence	
			FP-Growth	Apriori
1	8-08234-P99-A6NN1	9-09060-EXCHEM	78.7%	79.0%
2	M-AM24B-ROCK	9-09060-EXCHEM	75.0%	75.0%
3	X-EXC-CARB	9-09060-EXCHEM	71.8%	72.0%
4	X-EXC-CARB	M-AM24B-ROCK	70.9%	71.0%
5	M-AM24B-ROCK	X-EXC-CARB	62.9%	63.0%
6	9-0823-P99-A6NN1	M-AM24B-ROCK	62.5%	63.0%

7	9-09060-EXCHEM	M-AM24B-ROCK	62.4%	62.0%

Meanwhile, the association rules with 3 itemsets are obtained as shown in Table 7.

Table 7. Rapidminer 3 itemset test results

No	Premises	Condusion	Confidence	
			FP-Growth	Apriori
1	8-08234-P99-A6NN 1, X-EXC-CARB	9-09060-EXCHEM	83.3%	83.0%
2	8-08234-P99-A6NN 1, M-AM24B-ROCK	9-09060-EXCHEM	76.0%	76.0%
3	M-AM24B-ROCK, X-EXC-CARB	9-09060-EXCHEM	75.6%	76.0%
4	9-09060-EXCHEM, X-EXC-CARB	M-AM24B-ROCK	74.7%	75.0%
5	9-09060-EXCHEM, M-AM24B-ROCK	X-EXC-CARB	63.4%	63.0%
6	8-08234-P99-A6NN 1, 9-09060-EXCHEM	M-AM24B-ROCK	60.4%	60.0%

Conclusion

In this study, the researcher used one of the association rule data mining techniques, namely apriori and fp-growth, to provide recommendations on spare parts sales. The conclusion drawn from this study is as follows:

1. The results of association rules depend on the minimum confidence threshold used. The higher the minimum confidence threshold, the fewer association rules are generated.
2. The association rule results obtained using both the Apriori and FP-Growth methods produce the same combination patterns of parts.
3. In the research test using training data consisting of 9,851 data points, the final results yielded 6 rules, consisting of 3 rules for 2 itemsets and 3 rules for 3 itemsets.
4. In the research test using testing data consisting of 1,071 data points, the final result was 13 rules consisting of 7 rules for 2 itemsets and 6 rules for 3 itemsets.
5. The confidence values produced using the apriori and fp-growth methods differed by less than 0.5% due to the difference in decimals used.
6. The association rule data mining method can assist management in determining the combination of spare parts to be sold or in determining spare parts inventory.

Suggestion

The author's suggestions for this final project research are as follows:

1. Future research could be developed by using different minimum support and confidence calculations to determine whether they affect the results of the combination of parts.
2. Other researchers conducting research related to association rules should try using tools other than RapidMiner, such as Weka or other applications, so that the differences can be identified.
3. Future research can be developed using current year data so that the results can

be compared with the results of this study.

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