MATICS : Jurnal Ilmu Komputer dan Teknologi Informasi ISSN : 1978-161X(p); 2477-2550(e)
Volume 17, No. 1(2025), pp 12-18 DOI : 10.18860/mat.v17i1.28820
Received : August 28th 2020; **Accepted** : February 26th 2025 ; **Avalaible Online** : March 28th 2025

Market Basket Analysis Using FP-Growth and Apriori on Distro Store Sales Transaction

Umi Meganinditya Wulandari, Akrim Teguh Suseno, Muhammad Kholilurrahman

Abstract— **Market Basket Analysis analyzes consumer buying habits by finding relationships between items in the consumer's shopping basket. This Market Basket Analysis can provide success to the retail industry with the ability to understand consumer behavior and the speed of response to information obtained by retail business owners. This understanding is the result of an analysis that can help business owners improve marketing and sales strategies while utilizing transaction data. Sales transaction data that has been accumulated so far has only become data warehouses, while large amounts of transaction data can bring major changes to the level of competition in business and business actors in order to survive in the business world. In addition, after the COVID-19 outbreak, Indonesia experienced a slowdown in economic growth of 5.31%. This can be overcome by utilizing Market Basket Analysis to increase sales from their businesses. MBA with the methods used are FP-Growth and Apriori to analyze store transaction data in order to obtain association rules that can be used in improving marketing strategies. This analysis was carried out with 3 scenarios for 3 different minimum support values (1%, 2% and 3%) but the same minimum confidence value of 0.6 (60%). The comparison of the two methods is that 2 out of 3 scenarios produce the same association rule, namely 1 final association rule result with a lift value of 1.42. The three scenario results from both methods can be used by business owners as a consideration in determining sales strategies.**

Index Terms— **Apriori, Association Rules, FP-Growth, Market Basket Analysis.**

I. INTRODUCTION

THE development of information technology offers numerous benefits across various fields and contributes to the rapid amount of data stored in databases [1]. One example is in business competition, especially in the retail industry. Success in the retail industry is influenced by the ability to understand consumer behavior and the speed of response to information obtained by retail business owners [2]. Transaction data that has been accumulated so far has only become data warehouses, while large amounts of transaction data can bring major changes to the level of competition in business and business actors in order to survive in the competition [1]. In addition, after the COVID-19 outbreak, Indonesia experienced a slowdown in economic growth of 5.31%[3]. This problem can be overcome by increasing sales from their businesses [4]. The solution is to identify the most sold products and unsold products based on the purchasing patterns made by customers[2]. This problem can be solved by data mining. Data mining is a process that uses mathematical, statistical and machine learning techniques to identify and obtain useful information from a set of data [4]. The use of data mining is very necessary for retail businesses so that business problems and goals can be achieved [2]. Data mining uses an algorithm to process data with the aim of finding hidden patterns in the dataset [4], [5], [6]. This hidden pattern can be utilized by business owners. The technique that can find these patterns is association rules. Association rules are a rule-based machine learning technique used to find interesting relationships or patterns in a dataset. In the retail business, the association rules method is known as Market Basket Analysis [1].

Market Basket Analysis (MBA) is one of the Data Mining techniques used to analyze data and evaluate buyer tendencies in choosing products or services so as to find patterns or relationships between several items in the basket [4], [7]. MBA utilizes data by revealing the information contained therein to find frequent itemsets in sales transaction data [8]. Managed sales transaction data can produce information and be used for decision making [4].

FP-Growth and Apriori are two algorithms that is use for frequent itemset mining in association analysis. Although both aim to find frequently occurring itemsets in a transaction dataset, they have key differences in how they work. Some of the differences are taken from various aspects:

a. Use of Support Count

The FP-Growth method is more about avoiding Candidate Generation explicitly by generating candidate itemsets and calculating support at each iteration. FP-Growth works directly with the FP-

Manuscript received August 28, 20024. Umi Meganinditya Wulandari, author is with the Informatics Department of Nahdlatul Ulama Institute of Technology and Science, Pekalongan, Indonesia (corresponding author email nindityaw@gmail.com)

Akrim Teguh Suseno, author is with the Informatics Department of Nahdlatul Ulama Institute of Technology and Science, Pekalongan, Indonesia (e-mail akrim@itsnupekalongan.ac.id).

Muhammad Kholilurrahman, author is with the Informatics Department of Nahdlatul Ulama Institute of Technology and Science, Pekalongan, Indonesia (email ti15.0003@gmail.com)

Tree structure to find frequent itemsets without requiring candidate itemsets [9] while the Apriori method explicitly generates candidate itemsets (candidate generation) in each iteration and verifies the support of each candidate. This process is repeated for larger candidate itemsets until no more itemsets meet the support threshold [10].

b. Scalability on Larger Datasets
FP-Growth is more suitable for very large datasets because data compression through FP-Tree makes the mining process more efficient, both in terms of time and memory. This algorithm avoids exploration of irrelevant candidate itemsets [11] whereas in Apriori, candidate generation becomes very inefficient due to the large number of itemset combinations generated. The more items in the dataset, the more likely this algorithm will experience a drastic slowdown.

In this study, the methods used in MBA are FP-Growth and Apriori on the sales transaction data of the Sextors Distro Store. In 2000, Han proposed the FP-Growth algorithm [12]. FP-Growth uses the Tree concept in searching for the most frequently appearing data set or frequent itemset [13]. Research using FP-Growth has been conducted by Boby Septia Pranata on Motorcycle Workshop Spare Parts Inventory[13], Andi Ilhamsyah Idris on Wholesale Stores [14], Firmansyah on Book Sales Promotion [15], and Akrim Teguh Susone on MSMEs in the clothing sales sector [3] which produced patterns or frequent itemsets. The Apriori algorithm was first proposed by R. Agrawal and R. Srikant in 1994. Apriori is the basic and first algorithm used to find frequent itemsets [16]. Research using the Apriori algorithm has been conducted by Tina Kurniana on the Sakuyan Side Café Sales Transaction [17], M. Hamdani Santoso on the Minimarket Purchase Transaction [1], and Fajar Masya on the Point of Sales Application Sales Transaction [18] with the same goal of determining patterns or frequent itemsets. This study was conducted by analyzing the comparison of association rule results from the use of two methods, namely the FP-Growth and Apriori algorithms on the Sextors Distro Store Sales Transaction Data.

In the analysis stage, there are 3 scenarios carried out, namely the first scenario with a minimum support value of 0.01 (1%), the second scenario with a minimum support value of 0.02 (2%), the third scenario with a minimum support value of 0.03 (3%) and a minimum confidence value with a min_threshold of 0.5 (50%) for all scenarios. The results of the three scenarios from the two analyses were then compared with each other.

In this study, the discussion of the methods used is in section 2. The discussion of the implementation of the methods used through the workflow is in section 3. The discussion of the results obtained is in section 4. The discussion of the conclusions of the research conducted is in section 5.

II. METHOD

A. *Association Rules*

Association Rule Mining (ARM) is a technique for finding relationships between items in data that produces association rules between combinations of items [7]. Support is a measure of interest that shows the magnitude of the dominance of an itemset from all transactions that can be used in data mining. A measure of interest that shows the relationship between two items based on certain conditions that can be used in data mining is Confidence [19]. ARM is usually used in Market Basket Analysis (MBA). Market Basket Analysis is a modeling methodology that helps identify products that are likely to be purchased together by consumers [7]. This MBA process analyzes consumer buying habits by finding relationships between items in the consumer's shopping basket. The results of this analysis can help business owners improve their marketing strategies [19].

B. *FP-Growth Algorithm*

In 2000, Han proposed the FP-Growth algorithm [12]. FP-Growth uses the Tree concept in searching for the most frequently occurring data sets or frequent itemsets [13]. FP-Growth builds an FP-tree from a set of data and stores it in memory, then mines frequent itemsets by calling the FP-tree conditions recursively [20].

C. *Apriori Algorithm*

The Apriori algorithm was first proposed by R. Agrawal and R. Srikant in 1994. Apriori is the basic and first algorithm used to find frequent itemsets [16]. There are two benchmarks identified in Apriori, namely Support and Confidence. The percentage of itemset combinations is the Support value and the strength of the relationship between items in the association rule is the Confidence value. The determination of support and confidence values is as follows [19]:

$$support = \frac{number\ of\ transactions}{total\ transactions} \tag{1}$$

$$confidence = \frac{number\ of\ transactions\ A\ and\ B}{number\ of\ transactions\ A} \tag{2}$$

III. IMPLEMENTATION

A. *Workflow*

The study used quantitative methods using sales transaction data from the Sextors Disto Store. The data was input into this study and was analyzed using FP-Growth and Apriori so that the results could be compared to form association rules for creating marketing strategies. The following research stages were used as shown in Figure 1.

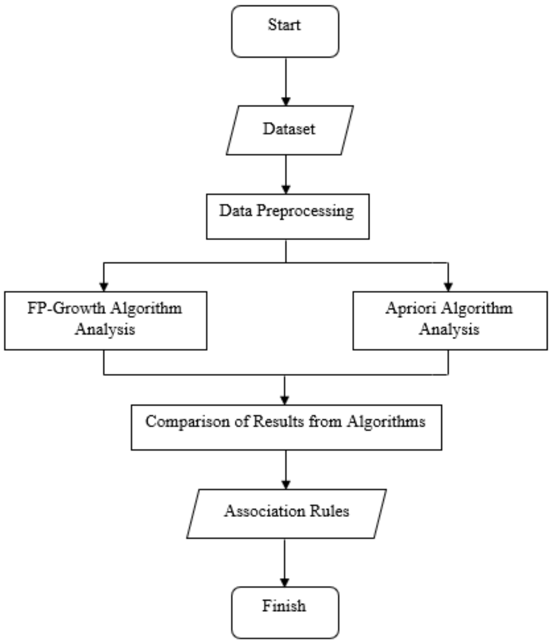

Fig. 1. Research Workflow

Figure 1 is a picture of the research workflow which start with data collection, data preprocessing, algorithm analysis, and finally the association rules as the final result of the research.

1. Dataset

The first stage of this research is data collection at the Sextor Distro Store. The data taken is sales transaction data during 2021.

2. Data Preprocessing

The second stage in the research is Data Preprocessing. At this stage, the data that has been obtained will go through two more stages, namely data cleaning and data transformation. These two stages are carried out with the aim of data cleaning to eliminate unused attributes, namely with 30 attributes becoming 2 attributes and data transformation to change data that was originally nominal data into numeric data (binomial data).

3. Analysis of FP-Growth and Apriori Algorithms

The third stage is to analyze the data that has gone through the preprocessing stage using two algorithms. In the analysis stage, there are 3 scenarios carried out, namely the first scenario with a minimum support value of 0.01 (1%), the second scenario with a minimum support value of 0.02 (2%), the third scenario with a minimum support value of 0.03 (3%) and a minimum confidence value with a min¬_threshold of 0.5 (50%) for all scenarios. The results of the three scenarios from the two analyses are then compared with each other.

4. Association Rules

This stage is the final stage. At this stage, it shows the final results of the research in the form of association rules with minimum support and minimum confidence values. The final results are association rules and lift values from the comparison of two algorithms which will later become considerations for business owners in creating marketing strategies.

IV. Result

This study uses data from a Distro Store named Sextors, Pekalongan Regency in 2021. The data obtained has attributes such as nourut, kode, kode barang, kd barang paket, nama barang, satuan, qty, harga, subtotal, point, point m, barang tambahan, saldo, hpp, satuan beli, isi, qty terima, ppn, diskon rupiah, jumlah ppn, no po, expired, komisi spg, posting, detail deb cc, detail disc global,detail tax, komisi sales, lokasistok, stok by ukuran warna. Here is an example of the data.

Table 1. Sales Data

nourut	KODE	…	stok_by_ukuran_warna
1	R43-130421001	…	FALSE
1	R43-130421002	…	FALSE
1	R43-130421003	…	FALSE
1	R43-130421004	…	FALSE

Sales data consists of 371 transactions and 30 attributes. Of these 30 attributes, only 2 are used in the analysis process, namely code (transaction code) and item code.

In data preprocessing, the dataset goes through a data cleaning process by removing attributes that are not needed in the data mining association rule analysis and removing transactions that only consist of 1 item. The results of this data cleaning process produce 371 transactions which then enter the next process, namely data transformation which changes data that was previously in the form of transaction data or nominal data as in Table 2. The following is for the transaction data.

Table 2. Transaction Data

Transaction ID	TRANSACTION
ID1	SE751, SE128
ID2	SE130, SE177
ID3	SE130, SE11
ID4	SE814, SE777, SE247
ID5	SE130, SE275, SE810
…	…
ID371	SE130, SE501

Transaction data such as Table 2. above is then changed into a numeric data table or in binomial form per transaction such as Table 3. The following is the changed data.

Table 3. Numerical Data (Binomial Data)

ID Trans	SE751	SE128	SE130	…	SE4007
ID1	1	1	0	…	0
ID2	0	0	1	…	0
ID3	0	0	1	…	0
ID4	0	0	0	…	0
ID5	0	0	1	…	0
…	…	…	…	…	…
ID371	0	0	1	…	0

Table 3 shows the results of the two processes which then become input to the next stage, namely the analysis stage using the FP-Growth and Apriori Algorithms. A value of 0 means "No" and a value of 1 means "Yes".

Next, we move on to the next stage, namely analysis using an algorithm. Analysis using both algorithms uses Google Colab with the Python programming language. This analysis stage, three scenarios were carried out, namely the first scenario with a minimum support value of 0.01 (1%), the second scenario with a minimum support value of 0.02 (2%), the third scenario with a minimum support value of 0.03 (3%) and a minimum confidence value with min_threshold 0.5 (50%) for all scenarios. The analysis stage uses the Python programming language. The meaning of min_threshold is referring to the minimum threshold value which means that when it is set as min_threshold, only itemsets that have a value greater than or equal to min_threshold will be considered. In the first scenario, the minimum support value is 0.01 (1%) with a limit of 10 itemsets as follows.

Table 4. Min Support Itemset Results Scenario 1 FP-Growth

No.	Support	Itemset
1.	0,162	SE128
2.	0,091	SE751
3.	0,421	SE130
4.	0,016	SE177
5.	0,029	SE11
6.	0,148	SE431
7.	0,154	SE822
8.	0,054	SE8003
9.	0,018	SE253
10.	0,04	SE19

In the second scenario, namely with a minimum support value of 0.02 (2%) with a limit of 10 itemsets as follows.

Table 5. Min Support Itemset Results Scenario 2 FP-Growth

No.	Support	Itemset
1.	0,162	SE128
2.	0,091	SE751
3.	0,421	SE130
4.	0,029	SE11
5.	0,043	SE431
6.	0,148	SE822
7.	0,154	SE8003
8.	0,054	SE253
9.	0,040	SE300
10.	0,108	SE241

In the third scenario, namely with a minimum support value of 0.03 (3%) with a limit of 10 itemsets as follows.

Table 6. Min Support Itemset Results Scenario 3 FP-Growth

No.	Support	Itemset
1.	0,162	SE128
2.	0,091	SE751
3.	0,421	SE130
4.	0,043	SE431
5.	0,148	SE822
6.	0,154	SE8003
7.	0,054	SE253
8.	0,040	SE300
9.	0,108	SE241
10.	0,056	SE790

The results of the three minimum support scenarios show the number of association rules shown in the following table.

Table 7. Results of Association Rules FP-Growth

No	Min Support	Min Confidence	Association Rules
1.	0,01%	0,5%	9
2.	0,02%		4
3.	0,03%		1

Table 7 shows that each minimum support has a different number of association rules. The following are the association rules in the first scenario, namely with a minimum support value of 0.01 (1%) and a minimum confidence value with a min_threshold of 0.5 (50%).

Table 8. Association Rules Results Scenario 1 FP-Growth

No.	Antecedents	Consequents	Support	Confidence
1.	SE11	SE130	0,016	0,54
2.	SE241	SE130	0,064	0,60
3.	SE131, SE241	SE130	0,018	0,70
4.	SE752	SE8003	0,010	1,00
5.	SSE815	SE130	0,021	0,72
6.	SE187	SE130	0,024	0,52
7.	SE131, SE187	SE130	0,010	1,00
8.	SE339	SE130	0,029	0,52
9.	SE8004	SE130	0,013	0,55

In the second scenario, namely with a minimum support value of 0.02 (2%), the minimum confidence value with a min_threshold of 0.5 (50%) shows the following association rules.

Table 9. Association Rules Results Scenario 2 FP-Growth

No.	Antecedents	Consequents	Support	Confidence
1.	SE241	SE130	0,064	0,60
2.	SSE815	SE130	0,021	0,72
3.	SE187	SE130	0,024	0,52
4.	SE339	SE8003	0,029	0,52

In the third scenario, namely with a minimum support value of 0.03 (3%), the minimum confidence value with a min_threshold of 0.5 (50%) shows the following association rules.

Table 10. Association Rules Results Scenario 3 FP-Growth

No.	Antecedents	Consequents	Support	Confidence	Lift
1.	SE241	SE130	0,064	0,6	1,42

The three scenarios can be seen that the greater the minimum support value, the fewer the number of association rules. The next stage is analysis using the Apriori algorithm.

It is the same as the analysis using the FP-Growth algorithm with three scenarios, namely the first scenario with a minimum support value of 0.01 (1%), the second scenario with a minimum support value of 0.02 (2%), the third scenario with a minimum support value of 0.03 (3%) and a minimum confidence value with min_threshold 0.5 (50%) for all scenarios. The meaning of min_threshold is referring to the minimum threshold value which means that when it is set as min_threshold, only itemsets that have a value greater than or equal to min_threshold will be considered. In the first scenario, the minimum support value is 0.01 (1%) with a limit of 10 itemsets as follows.

Table 11. Min Support Itemset Results Scenario 1 Apriori

No.	Support	Itemset
1.	0,421	SE130
2.	0,162	SE128
3.	0,154	SE8003
4.	0,151	SE131
5.	0,148	SE822
6.	0,129	SE501
7.	0,154	SE241
8.	0,091	SE751
9.	0,070	SE131, SE130
10.	0,064	SE130, SE241

In the second scenario, namely with a minimum support value of 0.02 (2%) with a limit of 10 itemsets as follows.

Table 12. Min Support Itemset Results Scenario 2 Apriori

No.	Support	Itemset
1.	0,421	SE130
2.	0,162	SE128
3.	0,162	SE8003
4.	0,151	SE131
5.	0,148	SE822
6.	0,129	SE501
7.	0,108	SE241
8.	0,091	SE751
9.	0,070	SE131, SE130
10.	0,064	SE130, SE241

In the third scenario, namely with a minimum support value of 0.03 (3%) with a limit of 10 itemsets as follows.

Table 13. Min Support Itemset Results Scenario 3 Apriori

No.	Support	Itemset
1.	0,421	SE130
2.	0,162	SE128
3.	0,154	SE8003
4.	0,151	SE131
5.	0,148	SE822
6.	0,129	SE501
7.	0,154	SE241
8.	0,091	SE751
9.	0,070	SE131, SE130
10.	0,064	SE130, SE241

The results of the three minimum support scenarios show the number of association rules shown in the following table.

Table 14. Apriori Association Rules Results

No	Min Support	Min Confidence	Association Rules
1.	0,01%	0,5%	5
2.	0,02%		4
3.	0,03%		1

Table 14 shows that each minimum support has a different number of association rules. The following are the association rules in the first scenario, namely with a minimum support value of 0.01 (1%) and a minimum confidence value with a min_threshold of 0.5 (50%).

Table 15. Association Rules Results Scenario 1 Apriori

No.	Antecedents	Consequents	Support	Confidence
1.	SE752	SE8003	0,010	1,00
2.	SE131, SE187	SE130	0,010	1,00
3.	SSE815	SE130	0,021	0,72
4.	SE131, SE241	SE130	0,018	0,70
5.	SE241	SE130	0,064	0,60

In the second scenario, namely with a minimum support value of 0.02 (2%), the minimum confidence value with a min_threshold of 0.5 (50%) shows the following association rules.

Table 16. Association Rules Results Scenario 2 Apriori

No.	Antecedents	Consequents	Support	Confidence
1.	SSE815	SE130	0,021	0,72
2.	SE241	SE130	0,064	0,60
3.	SE187	SE130	0,024	0,52
4.	SE339	SE8003	0,029	0,52

In the third scenario, namely with a minimum support value of 0.03 (3%), the minimum confidence value with a min_threshold of 0.5 (50%) shows the following association rules.

Table 17. Association Rules Results Scenario 3 Apriori

No.	Antecedents	Consequents	Support	Confidence	Lift
1.	SE241	SE130	0,064	0,6	1,42

The three scenarios can be seen to have similarities in the frequent itemset in scenarios 1 and 3. The number of association rules shows that the greater the minimum support, the fewer the number of association rules, which shows only 1 association rule with a minimum support of 0.03.

Table 18. Association Rules Results Different Apriori and FP-Growth

Method	Antecedents	Consequents	Support	Confidence	Lift
FP-Growth	SE241	SE130	0,064	0,6	1,42
Apriori	SE241	SE130	0,064	0,6	1,42

Based on the table above, it can be concluded that using the FP-Growth and Apriori methods produces the best and equally persistent values when applied to the SE241 itemset as the initial condition and the SE130 itemset as the final condition, so it can be concluded that the itemset is very suitable for using the FP-Growth or Apriori methods.

The results of the three scenarios using both algorithms show a decrease in the number of association rules generated from the minimum support value. This is due to the following:

a. As the minimum support value decreases, more itemsets qualify as frequent itemsets. The small minimum support value means that itemsets that appear less frequently will also be considered frequent itemsets.
b. The lower the minimum support value, the combination of association rules also increases, this is evidenced by the large number of association rules generated from the three scenarios that have been carried out.
c. The lower the minimum support value, the more data can be considered which may be important for certain analyses.

The results of the two algorithms show similarities in the number of association rules in scenarios 2 and 3 with the number of rules being 4 and 1. The results of scenarios 2 and 3 have the same Antecedents, Consequences, Support, Confidence. The difference between the two analyses is in scenario 1 which shows the number of association rules is 9 rules by the FP-Growth algorithm and 5 rules by Apriori. This is because FP-Growth uses a more efficient FP-Tree structure in storing and processing transaction information, this algorithm can find more frequent itemsets and consequently more association rules compared to Apriori. The candidate-based approach of Apriori tends to eliminate many itemsets in the early iterations, resulting in fewer association rules.

Both algorithms produce the same association rule, namely SE241 → SE130 with a support value of 0.06 and a confidence value of 0.6, which means that the support for SE241 purchased together (antecedents) with SE130 in one transaction is 6% (0.06) and there is a 60% (0.6) possibility that buyers will also buy SE130 (consequents) after buying SE241 in one transaction. The lift value in the analysis results is 1.42. This lift value shows a positive correlation between SE241 and SE130, which means that the presence of SE241 increases the likelihood of SE130. This positive correlation illustrates that SE130 is 1.42 times more likely to be purchased by customers who buy SE241. The rules generated by both algorithms provide insight into the relationship between the two items in the transaction dataset, helping sellers understand purchasing patterns and design more effective marketing strategies.

V. Conclusion

Based on the results of the comparative analysis of the FP-Growth and Apriori algorithms, both have the same Association Rules or purchasing patterns in the third and second scenarios. The third scenario produces one association rule, namely the item code SE241 → SE130 with a support value of 0.06, a confidence value of 0.6, and a lift value of 1.42, which means that the support for SE241 is purchased together (antecedents) with SE130 in one transaction of 6% (0.06), there is a 60% (0.6) possibility that buyers will also buy SE130 (consequences) after buying SE241 in one transaction and SE130 is 1.42 times more likely to be purchased by customers who buy SE241.

The comparison between this study and previous research, namely the research conducted by Firmansyah & Yulianto in 2021 on the book sales dataset [15] obtained the best results using the minimum support determination of 0.003 with the dominance of categories, namely law, comics, fiction, and children's books.

The results of this association rule can help the Sextors Distro Store in designing a more effective marketing strategy to increase sales. The result of market basket analysis is to find patterns of products that are frequently purchased together. From these results, merchants can use cross-selling and up-selling marketing strategies in their marketing strategies with the aim of increasing sales figures. In cross-selling, merchants can recommend complementary products that customers may be interested in, based on the customer's current purchases. Association rules can help by identifying products that are frequently purchased together. Up-selling involves encouraging customers to purchase a more expensive or premium version of a product they are considering. While association rules primarily help with cross-selling, they can also provide insight into related, more expensive products. Additionally, merchants can also create targeted ads or promotions for specific customer segments based on the identified purchasing patterns and correlations.

Based on the discussion in this study, the researcher's suggestion is that further research uses other algorithms in the Association Rules, uses different case studies, combine the FP-Growth or Apriori methods to produce the best results, optimize and modify both methods, and apply them to case studies to see if there is a positive effect on market profits.

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