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Utilizing association rule mining for enhancing sales performance in web-based dashboard application

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ABSTRACT

Data is increasingly recognized as a valuable asset for generating new insights and information. Given the importance of data, businesses must always look for ways to get more value from data generated from sales transactions. In data mining, association rule mining is a good standard technique and is widely used to find interesting relationships in databases. Association rule is closely related to market basket analysis to find items that often appear together in one transaction. This study proposes the frequent pattern growth (FP-Growth) algorithm in finding association rules on sales transaction data. Our methodology includes dataset preparation for modeling, evaluation of model performance, and subsequent integration into a web-based platform. We conducted a comparative analysis of the FP-Growth algorithm against the Apriori algorithm, finding that FP-Growth outperformed Apriori in efficiency. Using the same dataset and constraint level, both algorithms produce the same number of frequent itemsets. However, in terms of computation time, FP-Growth excels by taking 2.89 seconds while Apriori takes 5.29 seconds. We integrated trained FP-Growth algorithm into a web-based dashboard application using the streamlit framework. This system is anticipated to simplify the process for businesses to identify customer purchasing patterns and improve sales.

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1. INTRODUCTION

The rapid advancement of technology requires businesses to be more creative in developing strategies to adapt to competition. One strategy that can be implemented to win competition is by leveraging emerging technologies. Companies can leverage the data that is generated by information systems to assist in decision-making, including the development of sales strategies. To increase customer interest in making a purchase, it can be done by promoting a product with a promotion that causes someone who was previously not interested buying a product to become interested and trying to make a purchase [1].

One of many possible ways to process data into valuable information is through data mining. Data mining is a process that uses statistical, computational, artificial intelligence, and machine learning techniques to identify useful information and related knowledge from large databases [2], [3]. Data mining emerged to help decision-makers such as managers to develop marketing strategies and to identify relationships between items purchased by customers so that customer satisfaction can be improved.

Transaction data from sales processes can be refined in data mining using association rules. Association rules are a procedure to find relationships between itemsets in a given dataset [4], [5]. This technique is also known as market basket analysis. Market basket analysis is a methodology for analysing consumer buying habits by finding associations between different types of items that consumers place in their shopping basket during a particular transaction [6]. The Apriori and frequent pattern growth (FP-Growth) algorithms are two common methods used for association mining. The Apriori algorithm is used so that computers can learn association rules by finding patterns of relationships between one or more items in a dataset [7]. This algorithm requires scanning the database at each iteration. Therefore, the Apriori algorithm takes a longer time when it used large data. The FP-Growth is an alternative algorithm that can be used to determine the frequent itemset in a dataset [8]. The FP-Growth algorithm is a development of Apriori. The problems in Apriori are addressed by this algorithm by introducing a new and compact data structure often called a frequent pattern tree or frequent pattern tree (FP-Tree) [9]. The FP-Growth algorithm uses the concept of tree development to find frequent itemsets, which makes FP-Growth faster than Apriori.

Sivapriya *et al*. [10] conducted a study on the important contributions in the decision-making process and how decision makers must make some decisions with rapidly changing data. The results of the study found that the Apriori algorithm takes longer than FP-Growth. The purpose of this analysis is to provide insights for choosing the best decision by breaking down the problem into smaller parts but not simplifying the problem and being able to overcome the complexity of certain decisions. Harianto and Eddy [11] compared the Apriori and FP-Growth algorithms was conducted using an online retail dataset. The results showed that Apriori had better execution time efficiency, at 0.0424 seconds, compared to FP-Growth, at 0.0650 seconds. Although FP-Growth required more execution time, it produced more purchase patterns, at 256 rules, compared to Apriori, at 57 rules. This data mining method for analyzing purchase patterns is useful for businesses to ensure that their inventory is always sufficient to meet market demand. Hidayat *et al*. [12] used the Apriori and FP-Growth algorithms to analyze purchase patterns in cosmetics store transactions. The results found that the combination of products with the strongest support and confidence was original liquid bleaching seeds, Harva peeling gel, and castor oil distance oil. The Apriori algorithm took 1 hour and 34 minutes to execute, while FP-Growth took only 0.036 seconds. The study aimed to show that there is a need for a system that can help form product purchase pattern combinations using association rules to help in designing online store sales strategies to be more competitive. Islamiyah *et al*. [7] analyzed transaction data by comparing the Apriori and FP-Growth algorithms. The Apriori algorithm produced 11 rules with an execution time of 0.6 seconds, while FP-Growth produced 10 rules with an execution time of 0.5 seconds. Mythili and Shanavas [13] evaluated the performance of the Apriori and FP-Growth algorithms. Consequently, the execution time for both algorithms rise with an increase in data volume. Furthermore, at each tested minimum support value – 0.2, 0.4, 0.6, and 0.8 – the FP-Growth algorithm consistently requires less time compared to Apriori. This assessment demonstrates the greater efficiency of the FP-Growth algorithm over the Apriori algorithm.

Prior studies have demonstrated the successful implementation of FP-Growth and Apriori in extracting association rules from various datasets. Consequently, this study proposes FP-Growth and compare its performance with Apriori specifically on sales transaction datasets. Furthermore, none of the previous studies have integrated the trained model into web-based dashboard applications. In our study, the trained FP-Growth model will be seamlessly incorporated into a web-based application to enhance user convenience. The integration aims to facilitate businesses in identifying connections between products, making it easier for customers to purchase complementary items simultaneously. This information proves valuable for optimizing product layout and supporting the marketing strategy of maintaining a consistently available stock [7].

2. METHOD

In order to help computers discover association rules, association analysis is typically used to determine how items in a data set, or in this case, transactions, relate to one another [14], [15]. The method used in association rule by utilizing data mining techniques begins with understanding the importance of data and business, then collecting the necessary data and going through the data preprocessing stage before forming a model using the selected technique. Next, the performance of the algorithm on the model is evaluated, then the analysis results are visualized. Finally, the most optimal algorithm from the analysis results will be deployed on a web-based application.

2.1. Data collection and data preprocessing

To understand the problem, objectives, and needs from a business perspective, an understanding of the data mining that will be undertaken is needed [1]. This understanding is useful for determining the right strategy based on the results of data analysis so that decisions taken can have a positive impact on stakeholders and users. Furthermore, a comprehensive grasp of the business context enables the identification of key challenges and opportunities, guiding the data mining process effectively. By aligning data analysis outcomes with strategic goals, organizations can not only address existing issues but also proactively meet the evolving needs of stakeholders, fostering a more informed and adaptive decision-making environment.

The data collection stage consists of processes and techniques that are useful for extracting and collecting data from each data source. This study uses a public dataset that consists of transactions that occurred from December 1, 2010, to December 9, 2011. This dataset has been used in previous research [16] and can be accessed through the UCI machine learning website [17]. The dataset contains 541,909 rows and 8 columns, namely Invoice No, Stock Code, Description, Quantity, Invoice Date, Unit Price, Customer ID, and Country, as can be seen in Table 1. Furthermore, in the data preprocessing stage, the data is cleaned of erroneous values such as negative values, missing values, and data transformation so that the next process can be analysed, and the solution can be obtained. To obtain quality information, the preprocessing stage is very important in determining the future roadmap of efficient big data analysis approaches.

Table 1. Sample of dataset

No	Invoice no	Stock code	Description	Quantity	Invoice date	Unit Price	Customer ID	Country
1	536365	85123A	White hanging heart t-light holder	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
2	536365	71053	White metal lantern	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
3	536365	84406B	Cream cupid hearts coat hanger	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
4	536365	84029G	Knitted union flag hot water bottle	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
5	536365	84029E	Red woolly hottie white heart	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

2.2. Data modelling

Data modeling is done by forming association rules with the proposed FP-Growth algorithm. As one of the most important branches of data mining, association rule mining identifies associations and patterns that frequently occur between an itemsets in a given database [18]. This technique is used to build relationships between elements or characteristics in a very large database and calculate the likelihood of a particular product being purchased [19]. One of the algorithm used for generating association rules is FP-Growth [20], [21]. The FP-Growth algorithm, used for frequent itemset mining in data sets, operates in two major steps. Initially, it scans the dataset to identify the frequency of each item and sorts them in descending order, discarding items that do not meet a specified minimum support threshold. This results in a list of frequent items. Next, it constructs the FP-Tree, a compact structure that maintains the item association information. The tree is built by reading each transaction and mapping it onto the tree, with each path representing a set of items. Branches are shared among similar sets, which drastically reduces the space complexity. After the FP-Tree is constructed, the algorithm recursively divides the tree into conditional trees, each representing a conditional dataset for an item (or an itemset). It then mines these smaller trees individually, extracting the frequent itemsets from them. This approach eliminates the need to generate candidate sets, which is a computationally expensive step in other algorithms like Apriori, making FP-Growth efficient and scalable for large datasets.

In determining association rules, there is an interesting measure that is obtained from the results of data processing by calculating the values of support and confidence. In association rules, there is also the term antecedent and consequent. Association rules can have a number of items in the antecedent (left side) or consequent (right side) [2]. Methodology in determining the association analysis is divided into two stages:

a. High frequency pattern analysis

High frequency pattern analysis is a step to find a combination of items that meet a predetermined minimum support value. The support value can be obtained using the (1).

$$Support\ (X \rightarrow Y) = \frac{Number\ of\ transactions\ containing\ X\ and\ Y}{transactions\ total} \tag{1}$$

b. Association rule forming
Associative rule formation is done after finding all high-frequency patterns. Then look for associative rules that fulfil the minimum confidence value. The confidence value can be obtained using (2).

$$Confidence\ (X \rightarrow Y) = \frac{Number\ of\ transactions\ containing\ X\ and\ Y}{Number\ of\ transactions\ containing\ X} \quad (2)$$

After finding an association rule that fulfils the minimum support and minimum confidence requirements, the strength of the association rule can be seen by calculating its lift value. The lift value measures how important the rule that has been formed based on the support value and confidence value. A lift value greater than 1 indicates that X and Y appear together more often [22]. The lift value can be obtained using the (3).

$$Lift\ (X \rightarrow Y) = \frac{Confidence\ (X \rightarrow Y)}{Support\ (Y)} \quad (3)$$

2.3. Model performance evaluation

Time computation is an important performance metric for scientists and software engineers to determine whether an algorithm is capable of running within a reasonable time frame [23]. In the evaluation of the performance of association rules models, time computation refers to the time required by an algorithm to extract association rules from a dataset. This process involves steps such as scanning the dataset, forming itemsets, and identifying association rules. The evaluation of computation time is important to provide insights into the efficiency of the algorithm and how quickly the algorithm can provide results. Algorithms in data mining must be efficient and measurable to effectively extract information from large data sources. Efficiency, scalability, performance, optimization, and the ability to execute in real time are the key drivers for algorithm development [13]. As the size of the dataset increases, algorithms that can maintain relatively constant or linearly growing processing time are considered to be more effective than algorithms that require exponentially growing processing time.

2.4. Model visualization and deployment

Visualization is performed by taking the processed data that has passed through the previous stages, then the data is presented on the Streamlit platform. Streamlit is an open-source software framework used to create data science and machine learning applications [24]. The visualization of the analysis results is designed in such a way as to make it easy for users to understand the analysis results. The source code written using the python programming language is uploaded to GitHub so that Streamlit can read the source code provided. In that way, the web-based application that was originally only deployed locally using Streamlit can be accessed publicly through a web browser with a predetermined url. Web-based application is a computer program that runs on a web browser via an internet network and is comprised of clients and servers [25]. Web-based applications are very accessible to clients which makes them popular in this modern era. In addition, web-based applications can be accessed anywhere.

3. RESULTS AND DISCUSSION

3.1. Results analysis

The proposed FP-Growth was compared to Apriori using different minimum support and minimum confidence values. This was done to see the number of itemsets generated at each level of minimum support and minimum confidence for each algorithm. This comparative analysis aimed to understand how varying thresholds of minimum support and confidence affect the quantity of itemsets produced by both algorithms. By adjusting these parameters, the study could identify the efficiency and sensitivity of Apriori and FP-Growth in uncovering different patterns and associations within the data. The results are shown in the Table 2.

Referring to Table 2, it is evident that at each minimum threshold level, the quantity of itemsets produced by the two algorithms is identical. The highest count of itemsets is achieved at the lowest minimum support of 1% in this experiment, while the smallest count is at the highest minimum support of 10%. This occurrence is due to the minimum support value acting as a threshold for the frequency or support count that itemsets must achieve to be considered for rule formation. Thus, a higher minimum support value results in a reduced number of itemsets. Similarly, the number of itemsets generated is consistent across both algorithms at every minimum confidence level. The greatest quantity of itemsets was produced at a confidence level of 20%, whereas the peak confidence level of 80% resulted in the generation of 3 itemsets.

Ultimately, elevating the minimum confidence value corresponds to a reduction in the total number of itemsets created.

Table 2. Number of itemsets at a certain support and confidence level

No.	Support	Confidence	Total itemsets of FP-Growth	Total itemsets of Apriori
1.	1%	20%	838	838
		40%	453	453
		60%	146	146
		80%	22	22
2.	2%	20%	76	76
		40%	55	55
		60%	20	20
		80%	3	3
3.	3%	-	93	93
4.	4%	-	43	43
5.	5%	-	17	17
6.	6%	-	7	7
7.	7%	-	5	5
8.	8%	-	3	3
9.	9%	-	2	2
10.	10%	-	1	1

3.2. Model evaluation based on computation time

In evaluating the computation time of the Apriori and FP-Growth algorithms, the data is divided into several subsets. Starting from the first 40,000 records, the first 80,000 records, to the entire dataset used. This subdivision of data into progressively larger subsets allows for a detailed analysis of how each algorithm scales with increasing data size. By comparing the computation times at these different data volumes, insights into the efficiency and scalability of the Apriori and FP-Growth algorithms under varying workloads can be gained, as illustrated in Table 3.

The results of computation time prove that the FP-Growth algorithm is 45% faster than the Apriori algorithm. This figure is obtained from the time difference between the Apriori algorithm and FP-Growth, then divided by the computation time of the Apriori algorithm for entire dataset, that is (5.29-2.89)/5.29 = 0.45 or 45%. Figure 1 illustrates the comparative graph of the two algorithms' performance. The graph indicates that the computation time escalates with the enlargement of the dataset. For the Apriori algorithm, there is a markedly sharp rise in processing time, almost exhibiting an exponential increase as the data volume expands. Conversely, the FP-Growth algorithm demonstrates a relatively modest increase in processing time when compared to Apriori, highlighting its superior efficiency in handling larger datasets.

3.3. Model integration to web-based dashboard application

Once the most optimal model is identified based on the evaluation results, it is integrated into a web-based application designed for analyzing product purchase patterns. To enhance security measures and restrict access to authorized users, a login mechanism is implemented. Figure 2 displays the login page, where users are required to complete authentication forms by providing their username and password. This additional layer of security ensures that only authorized personnel can access and utilize the system, safeguarding sensitive information and maintaining the integrity of the application.

Table 3. Comparison of computation time of both algorithms

No.	Number of records	Time (s)	
		Apriori	FP-Growth
1.	40,000	0.44	0.27
2.	80,000	1.14	0.86
3.	120,000	1.34	0.91
4.	160,000	1.89	1.26
5.	200,000	2.11	1.52
6.	240,000	3.36	1.79
7.	280,000	3.97	2.06
8.	320,000	4.25	2.36
9.	360,000	4.47	2.62
10.	397,924	5.29	2.89

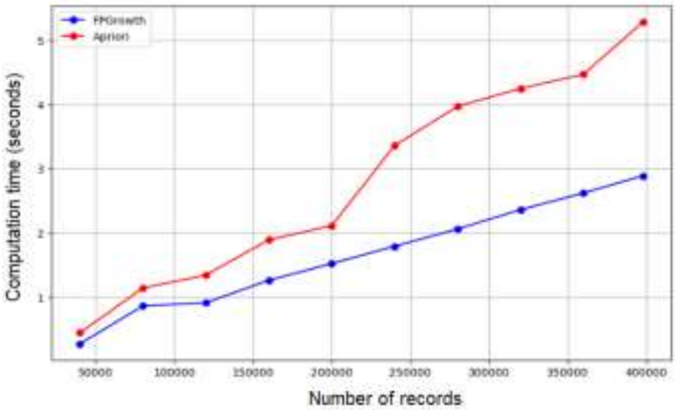

Figure 1. Comparison of computation time from both algorithms

Figure 2. Login page

Upon successful login, users gain access to a dashboard with a sidebar for data filtration. This sidebar allows users to choose specific items, define date ranges, and select particular hours for analysis. For those wishing to leave the application, a logout option is conveniently located in the same sidebar, as depicted in Figure 3. The process of filtering data leads to the generation of recommendations based on FP-Growth algorithm on prevailing purchasing patterns. Additionally, the dashboard displays key metrics such as total and average sales for the chosen dates. For users interested in preserving the results of these recommendations, there is an option to 'save data,' ensuring that insights can be reviewed later. The interface for viewing these recommendations is presented in Figure 4. This feature-rich dashboard not only aids in pattern analysis but also enhances the user's ability to make informed decisions based on the data presented.

Figure 3. Sidebar

Figure 4. Interface of recommendation results

Finally, the application features a detailed association rule table, showcasing items along with their corresponding support, confidence, and lift values, which can be viewed in Figure 5. The association table created by the FP-Growth algorithm provides a detailed overview of item relationships, highlighting patterns and connections discovered within the dataset. At the application's lower section, a 'saved data' table is provided for storing the outcomes of the recommendation analysis, including the values of support, confidence, lift, and a unique key for each entry. Users have the flexibility to remove any superfluous data by ticking the checkboxes in the 'select' column and then clicking the 'delete' button. This functionality aids in managing and maintaining the relevance of the stored data. The interface for this 'saved data' table is illustrated in Figure 6, offering a clear and user-friendly method for data management within the application. This enhances the overall usability of the tool, making it more efficient for users to handle large sets of recommendation results.

Figure 5. Interface of association rules

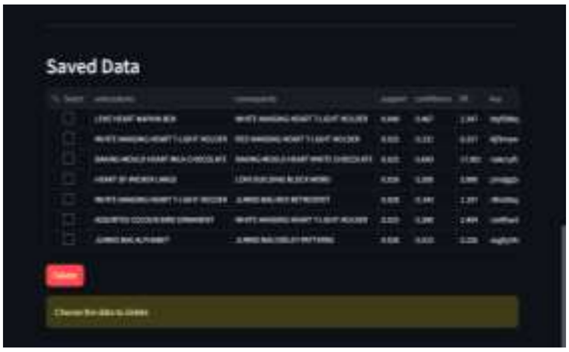

Figure 6. Interface of saved data table

4. CONCLUSION

Our study has shown that both the Apriori and FP-Growth algorithms generate an identical count of association rules at every threshold level in market basket analysis from sales transaction dataset. The FP-Growth algorithm stands out as it produces the same number of association rules as Apriori but in 45% less computation time. The effectiveness of recommendations for decision support can be gauged by examining the highest lift values of the association rules, as a higher lift value indicates a stronger correlation between items. Finally, the FP-Growth model has been effectively incorporated into a web-based platform using the Streamlit framework and Python programming language, providing users with an engaging and visually appealing way to view analysis results. The suggested system is anticipated to simplify the procedure for businesses in recognizing customer buying trends, consequently boosting sales through an optimized arrangement of products. Future research will involve contrasting the performance of different algorithms in association rule mining and exploring additional variables beyond transaction data, such as weather conditions and customer behavior. This expanded analysis aims to understand the broader impact of various external factors on purchasing patterns.

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