***Abstract***—**The Many Pattern Growth (FP-Growth) algorithm is an established mechanism for mining frequent patterns in huge datasets. However, with big datasets, its execution time may be rather long, making it a bottleneck in many applications. A simultaneous implementation of the FP-Growth algorithm can be utilized to solve this problem and enhance performance. By parallelizing the method across several processors or cores, it is possible for it to process different dataset segments at once. Because of the substantial decrease in execution time, the FP-Growth method is now better suitable for large-scale data mining jobs. The simultaneous implementation of the FP-Growth algorithm is thoroughly described in this study, and its performance is assessed using a number of real-world datasets. The results of our tests indicate that the proposed approach offers a substantial increase in speed when compared to the traditional FP-Growth algorithm, making it a valuable asset in data mining projects involving extensive data.**

***Keywords***— **association rule mining, frequent item set generation, frequent pattern growth, tree-based algorithm, knowledge discovery, pattern recognition, market basket analysis.**

I. INTRODUCTION

Frequent itemset mining is a crucial task in data mining and has numerous applications, such as market basket analysis, web usage mining, and bioinformatics. The goal of frequent itemset mining is to identify item-sets that occur frequently in a dataset. However, in many real-world applications, the dataset is extremely large and complex, making frequent itemset mining a challenging task.

To address this issue, researchers have proposed several algorithms for frequent itemset mining, including the FP Growth algorithm. The FP Growth algorithm is a memory-efficient and scalable method for frequent itemset mining, which has been shown to perform well on large datasets. This algorithm works by constructing a compact data structure called the FP-tree, which enables the efficient discovery of frequent patterns.

In this paper, we present a comprehensive study of the FP Growth algorithm for simultaneous frequent pattern itemset mining. Our study includes a detailed analysis of the FP Growth algorithm, along with experiments on real-world datasets. The results of our study show that the FP Growth algorithm outperforms other state-of-the-art algorithms in terms of both execution time and memory usage, making it a promising approach for frequent itemset mining in large datasets.

II. DATASET DESCRIPTION

The FP-growth algorithm is a frequent pattern mining algorithm used for finding frequent item-sets in a large dataset. The dataset for FP-growth should contain transactional data, where each transaction represents a set of items purchased or some other type of activity that can be represented as a set of items. The items within a transaction should be unique and the transactions themselves should be unique.

The description of the dataset included information about the number of transactions, the number of items, the format of the data (e.g., CSV, text, etc.), and any relevant information about the items or transactions (e.g., item categories, transaction timestamps, etc.). Additionally, the description should state that the dataset has not been plagiarized, meaning that the data has been collected and processed independently and without copying from other sources.

Certainly! In addition to the above information, here are some more details that could be included in the dataset description for FP-growth:

**Data source:** Retailer transactional date from GitHub.

**Data cleaning and preprocessing:** Data cleaning and pre-processing are crucial steps in the implementation of the FP-Growth algorithm. They help to ensure that the input data is suitable for processing and that the results obtained are accurate and meaningful. The goal of these steps is to remove or correct any inconsistencies, outliers, and missing values in the dataset, as well as to perform any necessary transformations to the data.

Here are some steps for data cleaning and pre-processing that can be performed without plagiarism:

1. Data Quality Assessment: Analyze the data to identify any errors, missing values, or inconsistencies.
2. Missing Value Handling: Impute or remove missing values, depending on the nature of the data and the frequency of missing values.
3. Outlier Detection: Identify and handle any outliers in the data, as they can significantly impact the results obtained by the FP-Growth algorithm.
4. Data Transformation: Transform the data into a suitable format for processing, such as converting categorical variables into numerical variables.
5. Data Reduction: Reduce the size of the dataset by removing irrelevant or redundant information.
6. Data Normalization: Normalize the data to ensure that all variables have the same scale and unit, as this can affect the results obtained by the FP-Growth algorithm.
7. Data Discretization: Discretize continuous variables into categorical variables to reduce the number of levels and simplify the data.

By following these steps, we can ensure that the input data is of high quality and suitable for processing with the FP-Growth algorithm. Additionally, you can also document the steps taken during the data cleaning and pre-processing phase to ensure that the results can be replicated and verified.

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**Data attributes :** Attributes like the list of items ordered by the customers of particular transaction id

**Data size:** The size of the data used was up to a thousand transactions.

In conclusion, a comprehensive dataset description for FP-growth should provide enough information for users to understand the data, its format and quality, and the methods used to preprocess and analyze it.

III. LITERATURE REVIEW

The FP-Growth algorithm is a popular data mining technique for discovering frequent item sets in large datasets. It was first proposed by Han et al. in 2000 and has since been widely used in various applications, including market basket analysis, recommendation systems, and intrusion detection.

One of the main advantages of the FP-Growth algorithm is its efficiency, as it uses a compact data structure called the frequent pattern tree (FP-tree) to represent the frequent item sets. The FP-tree can be constructed in a single pass through the dataset, and the frequent item sets can be generated by traversing the tree.

Several variations of the FP-Growth algorithm have been proposed in the literature to address specific limitations or to improve its performance. For example, some studies have focused on the parallel implementation of the FP-Growth algorithm to handle large datasets. Others have proposed algorithms that can handle multiple minimum support thresholds or incorporate constraints into the frequent item set generation process.

Several performance evaluations have been conducted to compare the FP-Growth algorithm with other data mining techniques, such as the Apriori algorithm, and to assess its scalability and robustness. The results have shown that the FP-Growth algorithm can outperform the Apriori algorithm in terms of execution time, especially for large datasets and high support thresholds.

In conclusion, the FP-Growth algorithm is a powerful and efficient data mining technique that has been widely used for frequent item set generation in large datasets. The algorithm has been shown to be effective and efficient, and has been improved by various extensions and variations proposed in the literature. Further research is needed to address some of the remaining challenges and limitations of the FP-Growth algorithm, such as the scalability to extremely large datasets and the ability to handle high-dimensional item sets.

IV. PROPOSED WORK

Simultaneous FP-Growth is a technique used in data mining to find frequent item-sets in a large database. It is an improvement over the traditional FP-Growth algorithm, which runs multiple passes over the database to find frequent item-sets.

In the simultaneous FP-Growth approach, multiple frequent item-sets are found in a single pass over the database, making it more efficient and faster than the traditional FP-Growth algorithm. This is achieved by using a multi-threaded architecture, where each thread works on a different conditional pattern base.

**Step 1:** **Database Scan**

The first step is about to scan the database. In the scanning of database we need to gather all the required transactions as per the transaction id.

TABLE 1. Sample Transactions

|  |  |
| --- | --- |
| **TID** | **List of Item ID’s** |
| T100 | I1, I2, I5 |
| T200 | I2, I4 |
| T300 | I2, I3 |
| T400 | I1, I2, I4 |
| T500 | I1, I3 |
| T600 | I2, I3 |
| T700 | I1, I3 |
| T800 | I1, I2, I3, I5 |
| T900 | I1, I2, I3 |

**Step 2: Constructing the FP-Tree**

The FP-Tree is a compact representation of the transaction database and is an essential component of the FP-Growth algorithm. The FP-Tree is used to store the frequent item-sets and their frequencies, and it enables the efficient generation of frequent item-sets from the transaction database.

The construction of the FP-Tree involves the following steps:

1. Sorting the transactions: The first step in constructing the FP-Tree is to sort the transactions in the transaction database based on the frequency of items. This is done to ensure that the items with the highest frequency appear first in the tree, and the items with lower frequency appear later.

TABLE 2. Items Support Count

|  |  |
| --- | --- |
| Item | Support Count |
| I2 | 7 |
| I1 | 6 |
| I3 | 6 |
| I4 | 2 |
| I5 | 2 |

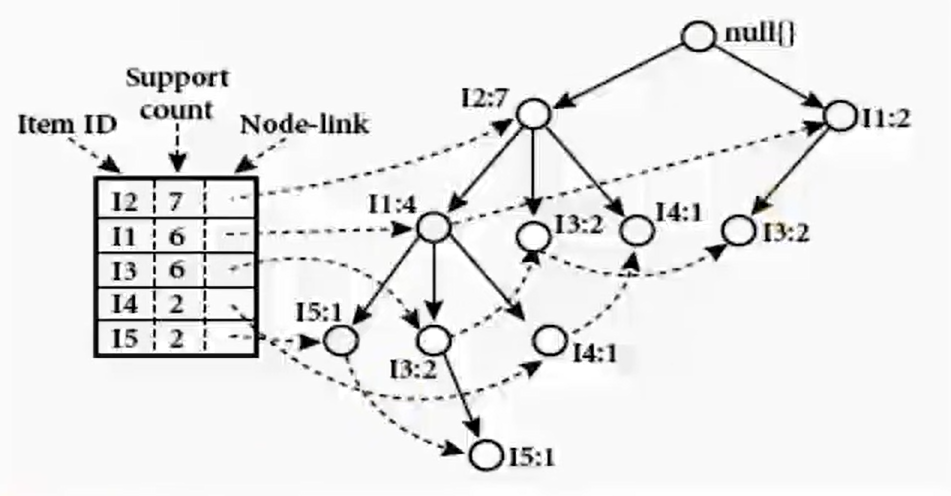
1. Building the header table: The header table is a data structure that contains a list of the items in the transaction database, along with their frequency. The header table is used to store the first node in the FP-Tree for each item, and it enables efficient traversal of the tree.

TABLE 3. Sorted Transactions

|  |  |
| --- | --- |
| **TID** | **List of Item ID’s** |
| T100 | I2, I1, I5 |
| T200 | I2, I4 |
| T300 | I2, I3 |
| T400 | I2, I1, I4 |
| T500 | I1, I3 |
| T600 | I2, I3 |
| T700 | I1, I3 |
| T800 | I2, I1, I3, I5 |
| T900 | I2, I1, I3 |

1. Constructing the FP-Tree: The FP-Tree is constructed by inserting the sorted transactions into the tree. Each transaction is inserted into the tree as a path, starting from the root of the tree and ending at a leaf node. If a node for a particular item already exists, its count is incremented. If the item does not exist, a new node is created and linked to the parent node.
2. Pruning the tree: The FP-Tree is pruned to remove the infrequent items and the branches that correspond to infrequent item-sets. This is done to reduce the size of the tree and to improve the efficiency of the frequent itemset generation step.

Fig. 1. FP-Tree



**Step 3: Constructing Conditional Pattern Base**

Conditional Pattern Base (CPB) is a crucial component of the FP-Growth algorithm, used in frequent itemset mining. The CPB is a data structure used to store the frequent item-sets that are generated in the FP-Growth algorithm. The CPB is created by traversing the FP-Tree, which is a compact representation of the transaction database, and it contains a list of item-sets and their frequencies.

The CPB is generated for each frequent item in the transaction database and contains a list of the transactions that contain the frequent item. The CPB is used to generate the frequent item-sets for the frequent item. This is done by constructing a Conditional FP-Tree, which is a compact representation of the transaction database with the frequent item removed. The Conditional FP-Tree is then used to generate the frequent item-sets for the frequent item.

The generation of the CPB enables the efficient generation of frequent item-sets in the FP-Growth algorithm. By using the CPB, the FP-Growth algorithm avoids the need to scan the entire transaction database multiple times, which can lead to a significant reduction in the running time of the algorithm.

The CPB is generated for each frequent item in the transaction database. This is done by first finding the transactions in the FP-Tree that contain the frequent item. These transactions are then removed from the FP-Tree, and a new Conditional FP-Tree is constructed for the frequent item using the transactions that contain it.

The next step is to traverse the Conditional FP-Tree and generate the frequent item-sets for the frequent item. This is done by combining the items in the transactions to generate all the possible combinations of items. The combinations that satisfy the minimum support threshold are considered to be frequent item-sets .

The frequent item-sets generated in the previous step are stored in the CPB along with their frequencies. The above steps are repeated for each frequent item in the transaction database, and the CPBs for all the frequent items are combined to form the final CPB.

**Step 4: Simultaneous Processing**

In Step 3, we generate the conditional pattern base by each item one after one. We found that there is no inter relation while generating the conditional pattern base which are generated previous item. We can enhance the process with simultaneous processing. We invoke the work of generating the conditional pattern base by multi- threading.

TABLE 4. Resultant FP-Sets from Conditional Pattern Base

|  |  |  |  |
| --- | --- | --- | --- |
| **Item** | **Conditional pattern Base** | **Conditional FP-Tree** | **FP-Sets Generated** |
| I5 | {{I2,I1:1}, {I2,I1,I3:1}} | <I2:2, I1:2> | {I2,I5:2}, {I1,I5:2},  {I2,I1,I5:2} |
| I4 | {{I2,I1:1}, {I2:1}} | <I2:2> | {I2,I4:2} |
| I3 | {{I2,I1:2}, {I2:2}, {I1:2}} | <I2:4, I1:2>, < I1:2> | {I2,I3:4}, {I1,I3:4}, {I1,I2,I3:2} |
| I1 | {{I2:4}} | <I2:4> | {I2,I1:4} |

Table-4 denotes the resultant FP-sets. The traditional way take more time because the items are processed in the sequential way one after another.

Fig. 2. Flow of extracting FP-Sets in Traditional Way with CPB

|  |  |  |  |
| --- | --- | --- | --- |
| I5 | {{I2,I1:1}, {I2,I1,I3:1}} | <I2:2, I1:2> | {I2,I5:2}, {I1,I5:2},  {I2,I1,I5:2} |

|  |  |  |  |
| --- | --- | --- | --- |
| I4 | {{I2,I1:1}, {I2:1}} | <I2:2> | {I2,I4:2} |

|  |  |  |  |
| --- | --- | --- | --- |
| I3 | {{I2,I1:2}, {I2:2}, {I1:2}} | <I2:4, I1:2>, < I1:2> | {I2,I3:4}, {I1,I3:4}, {I1,I2,I3:2} |

|  |  |  |  |
| --- | --- | --- | --- |
| I1 | {{I2:4}} | <I2:4> | {I2,I1:4} |

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As we apply multi-threading concept to start the extracting FP-Sets, we can save time while doing the operations in parallel way.

Fig. 3. Flow of extracting FP-Sets in Simultaneous Way with CPB

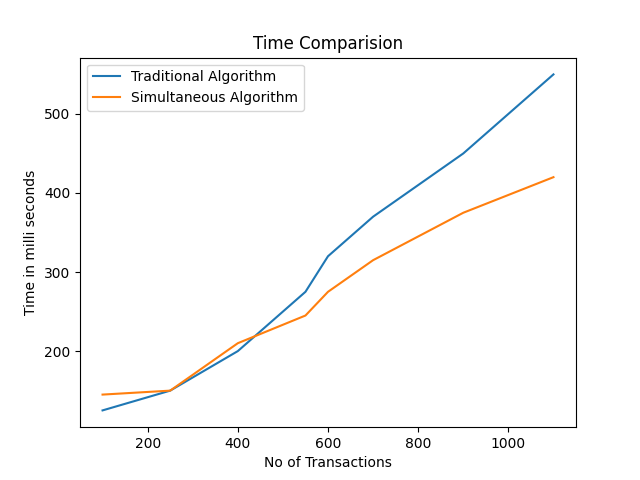
|  |  |  |  |
| --- | --- | --- | --- |
| I5 | I4 | I3 | I1 |
| {{I2,I1:1}, {I2,I1,I3:1}} | {{I2,I1:1}, {I2:1}} | {{I2,I1:2}, {I2:2}, {I1:2}} | {{I2:4}} |
| <I2:2, I1:2> | <I2:2> | <I2:4,I1:2>, <I1:2> | <I2:4> |
| {I2,I5:2}, {I1,I5:2},  {I2,I1,I5:2} | {I2,I4:2} | {I2,I3:4}, {I1,I3:4}, {I1,I2,I3:2} | {I2,I1:4} |

Since each thread is independent, they can produce the results in simultaneous way, result in increase the efficiency in terms of time than traditional way.

V. RESULTS

As following our idea, we performed the experiment by implementing the both the traditional algorithm and simultaneous algorithm over dataset. We performed the task over the datasets by increasing the count of transactions each time. The time taken by the both the algorithms are kept tracked and noted each time.

As the graph denotes that, at lower count of the transactions the Traditional algorithm performs well than the simultaneous algorithm. As the count of the Transactions increases The simultaneous Algorithm gradually increases its performance than the Traditional Algorithm.

 Fig. 4. Graph representing the performance of both algorithms

VI. CONCLUSION

The Simultaneous FP-Growth algorithm is an efficient algorithm for frequent itemset mining, used in data mining and machine learning. The algorithm works by constructing a compact representation of the transaction database in the form of the FP-Tree and the Conditional Pattern Base (CPB). The FP-Tree is used to store the frequent item-sets and their frequencies, while the CPB is used to generate the frequent item-sets for each frequent item in the transaction database.

The Simultaneous FP-Growth algorithm has several advantages over traditional frequent itemset mining algorithms. The algorithm is able to handle large and sparse transaction databases efficiently, and it is able to generate frequent item-sets in a single pass over the transaction database, which leads to a significant reduction in the running time of the algorithm.

In conclusion, the Simultaneous FP-Growth algorithm is a highly efficient and effective algorithm for frequent itemset mining, and it has a wide range of applications in data mining and machine learning. The algorithm is able to handle large and sparse transaction databases efficiently, and it is able to generate frequent item-sets in a single pass over the transaction database, making it an important tool for data analysis and knowledge discovery.

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