International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2019 IJSRCSEIT | Volume 5 | Issue 3 | ISSN : 2456-3307
DOI : https://doi.org/10.32628/CSEIT1953162

An Efficient Method for Frequent Itemset Mining on Temporal Data

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ABSTRACT

Frequent itemset mining (FIM) is a data mining idea with extracting frequent itemset from a database. Finding frequent itemsets in existing methods accept that datasets are static or steady and enlisted guidelines are pertinent all through the total dataset. In any case, this isn't the situation when information is temporal which contains time-related data that changes data mining results. Patterns may occur during all or at specific interims, to limit time interims, frequent itemset mining with time cube is proposed to manage time arranges in the mining technique. This is how patterns are perceived that happen occasionally, in a period interim, or both. Thus, this paper mostly centres around developing up a productive calculation to mine frequent itemsets and their related time interval from a value-based database by expanding from the earlier calculation dependent on support and density as another edge. Density is proposed to deal with the overestimated timespan issue and to ensure the authenticity of the patterns found. As an extension from the current framework, here the density rate and minimum threshold is dynamically generated which is user determined parameter previously. Likewise, an analysis concerning time is made between dataset with partitioning and without apportioning the dataset, which shows computation time is less on account of partitioning technique.

Keywords : Extended Apriori Algorithm, Density, Dynamic Generation, Temporal Pattern, Frequent Itemset Mining, Time Cubes, Partitioning

I. INTRODUCTION

Data mining (sometimes referred to as data or knowledge discovery) is the way toward examining and condensing data from unique perspectives into helpful finding. In general, the path toward finding connections or patterns among wealth of fields in tremendous social databases is data mining. One of the huge endeavours in data mining is Frequent Itemset mining (FIM). The key undertaking of information mining is to investigate the database to discover consecutive, frequent patterns.

To mine knowledge from the current dataset and to transform it into the user-friendly form is the main purpose of data mining. The ability of conventional data mining systems to document and system time-various aspects of real-world databases is one of the important features ignored. In simple words, the conventional data mining strategies need in their capacity to examine variety of information after some time and treat them as common information. But this is not case when information is temporal, temporal data contains data that are related to time. Financial exchange information, manufacturing or generation information, maintenance data, web mining and point-of-sale records are some of the examples of temporal datasets. Because of the significance and multifaceted nature of the time property, a variety of sorts of patterns are of interest. One of the principle expansions to data mining is temporal data mining which has the capacity to incorporate time attribute analysis. In data mining, evaluation of Transactional data is one of the most important application.

Owing to the increase in amount of stored data, a lot of interest in the discovery of hidden information has evolved in the last ten years. This revelation has been centred for the most part around data clustering, data classification. Treating information having temporal characteristics, is a significant issue that emerges amid mining. As we know that in temporal characteristics the information is mainly related to time. These attributes need to be handled separately and differently from other attributes. Temporal information mining is a noteworthy bit of data mining. It is extraction of certain, possibly significant and heretofore unspecified information, from gigantic proportion of data. Worldly data mining manages the information mining of enormous successive informational collections. Basically, the temporal database, for the most part incorporates two mine viewpoints, valid time and transaction time. During a timespan when a reality is valid regarding this present reality then it ought to be a valid time. Transaction time is the timespan during which a reality is put away in the database.

Frequent itemset mining on temporal data is an emerging topic in data mining. Discovering frequent itemset is time consuming. To find each item in transaction along with the Time cube information is time consuming task. As of now, we understand that Frequent Itemset Mining (FIM) has been an essential bit of information investigation and information mining. FIM endeavours to extract information from databases dependent on frequently occurring events, i.e., an event, or a set of events, is interesting.

Numerous algorithms exist that performs FIM productively on distributed information, for example, Apriori. Many improved types of Apriori calculations are created as of late. In all such cases, still there are a few issues exist in frequent itemset mining, that it not deals with huge measure of data because of higher time complexity nature. Much of the time, however, calculation ends up being immovable dependent on the user-specified threshold. To conquer these issues numerous specialists have built up an algorithm that plans to decrease generally speaking computational time. Extraction of frequent Itemset from a transaction data is a significant undertaking in information mining. The transaction entries vary periodically. Frequent Itemset mining need to be done based on temporal information. Frequent itemset mining in a ton of data is One of the critical troubles found in these days. There is need to develop effective time specific frequent Itemset extraction. Time interval specific frequent Itemset needs to be extracted from dataset.

Mining of frequent itemsets has been generally utilized in transactional databases for a considerable length of time. The traditional technique involves mining frequent itemsets on all records present at once in the transaction database. This caused performance issues such as out of memory, large computation turnaround time. The aim of the study is to propose suitable technique to overcome memory issues, reduce overall turnaround time and enable the determination of frequent itemsets based on a time frame.

The organization of this document is as follows. In Section 2 (**Related Work**), explains some related work done in frequent itemset mining using different methods. Section 3 (**Methods and material**), deals with proposed algorithm which is presented in detail. The idea of TCs is explained and the essence of a density threshold is illustrated and the partitioning approach is also discussed in detail. In Section 4 (**Result and Discussion**), deals with the results and a brief analysis on experimental results are described and finally in Section 5 (**Conclusion**), it is explained with the future scope.

II. RELATED WORK

There are lots of research work done in mining frequent itemsets using different algorithms in recent years. A Brief reviews of some of those recent significant researches are presented below:

Essalmi, Houda, et. al., [1], introduces an algorithm called, AprioriMin Algorithm which mines the frequent itemsets. This calculation goes for presenting another system for the computation of continuous itemsets to prune period of frequent itemsets. This procedure diminishes the execution time, when the support threshold increments for AprioriMin Algorithm.

Panita, Thusaranon et. al., [2], they have proposed a gradual subsistence that can deal with instance of record inclusion and cancellation all the while. The proposed algorithm predicts planned frequent itemsets by utilizing random walk procedure and update frequent itemsets when exchanges are included or erased from the database.

Moens et. al., [6], the authors used two techniques for mining frequent itemsets in parallel on the MapReduce framework where recurrence limits can be set low. First technique, called Dist-Eclat, is a pure Eclat strategy that circulates the inquiry space as equally as conceivable among mappers. This technique can mine enormous datasets, yet can be restrictive when managing massive amounts of information. In this way, present a moment, half and half strategy that first uses an Apriori based method to concentrate visit itemsets of length k and later on changes to Eclat when the projected databases fit in memory and call this calculation BigFIM.

Singh et. al., [5], expected to improve the execution of apriori algorithm by lessening the size of database and presented another characteristic Size of exchange (SOT) that takes the estimation of number of things in individual exchange in database. The deletion process of the transaction takes place accordance to the value of k. Remove those transactions from the database only if the value of k matches with the value of SOT.

Chen et. al., [4], introduced pruned optimization strategy. With this technique, it decreases the generation of frequent itemsets and also, transaction deduction is utilized to compact the transaction of a database. The estimation of the support chose is expanding which brings about lessening number of frequent itemsets produced.

Saleh, B. and Masseglia et. al., [7], finds the subset of dataset containing more frequent itemset. For e.g. items purchasing is more in Christmas than the summer. It dynamically determines the period by analysing frequency of itemset. By traditional methods the itemset support might be less by considering the whole dataset. This technique is useful for seasonal product purchase behaviour analysis.

III. METHODS AND MATERIAL

A. Introduction

Data mining is utilized to discover patterns that are interesting and knowledge from huge measure of information. Mining frequent patterns on temporal data is tedious task. Finding frequent item sets using conventional techniques makes mining even more complex. when the data is temporal, it contains temporal patterns i.e. contains time-stamped data. Discovering frequent patterns from temporal data will be a time-consuming task in the entire data mining process. So, developing an efficient method for this data mining problem is the only way for solving this issue. The problem is to discover valid time intervals during which frequent patterns hold.

Ghorbani and Abessi [3] illustrated that when data is temporal it contains time-related information that transforms data mining results. Since information is temporal, so patterns may occur during all or few intervals, so as to confine time intervals, the algorithm called frequent itemset mining with time cubes is proposed. Time cubes are used to handle time hierarchies. This is the way patterns are recognized that occur during a particular time interval. The paper mainly focuses on developing an efficient algorithm to mine frequent itemsets and their related time interval by extending apriori based on density and support as new threshold. To deal with overestimating time period problem and to check the validity of patterns found using density threshold.

To overcome the limitations of existing system, density rate and minimum support are generated dynamically which is user-defined parameter before. So that it will be more useful in the mining process of frequent itemsets and more effective for finding frequent itemsets. Also partitioning technique is used. Partitioning the whole dataset is done to reduce the computational time. Comparison is made between partitioning and without partitioning the dataset with respect to time where the graphs shows that the computational time is less in the case of partitioning technique.

B. Mining Frequent Patterns with Time Cubes

This section describes the methods used to mine frequent itemset mining on temporal data and also explains proposed algorithm for mining frequent itemsets.

Let I = {i1, i2, . . . in} be a set of items and C be a database of transactions. Each transaction tr is associated with an identifier transaction ID (TID), a time stamp T_{tr} and a set of items. For all transactions, $T_{tr} \in$ TS, where TS is the total time span of the database. Let t_{st}, $t_{et} \in$ TS where t_{st} is the start time and t_{et} is the end time be the time interval in each time hierarchy and also it is clear that $t_{st} < t_{et}$. For example, $(5,8)_{Month}$ shows the time interval between 5th and 8th months. In order to deal with temporal parts of the transactions, TC is defined. Cubic structure for time hierarchy encourages us to effectively merge neighbouring frequent itemsets to discover distinctive temporal patterns. Each Time Cube represents a time interval with different time hierarchies.

For time hierarchies more than three, the term hypercube is used instead. Minimum interval is defined by the user for an equivalent length partitioning, knowing time progression and its space. These initial cubes are called Basic Time Cubes (BTCs). Since rules can occur during a very narrow time interval, it is important to specify a minimum time interval to partition the database. One can consider one hour, one day, one month to define a 1 × 1 × 1 BTC. Any two elements in BTC cannot be overlapped such that $BTC_i \cap BTC_j = \varphi$

Let $|N^{Cube}|$ be the number of transactions occurred in the cube, i.e., time interval, and $|\ N\ (X)^{Cube}\ |$ be the number of transactions containing itemset M. The support of itemset M is calculated as follows:

$$\text{Support (M)} = \frac{|\ N\ (X)^{Cube}|}{|\ N^{Cube}\ |} \qquad (1)$$

According to above formula, now define support of each frequent itemset as follows:

$$\text{Support } (M \Longrightarrow^{Cube} N\ ) = \frac{|\ N\ (M,N)^{Cube}|}{|\ N^{Cube}\ |} \qquad (2)$$

Where $|\ N\ (M,\ N)^{\ Cube}\ |$ is the number of transactions which contains both M and N in that time interval.

Minimum support is a threshold to evaluate itemsets. As support is the proportion of an itemset in that cube to the total number of transactions in that cube. So here we are increasing minimum support threshold if the transactions are more and the value is decreasing when it is less. By this way it can be generated dynamically. Since records are not equally distributed in time intervals, very few records may occur in some occasions. Therefore, discovered patterns may not be valid, since there is not enough evidence to show that they hold for the time interval. It also causes overestimating problem. So as to overcome these issues, another threshold which is called density is proposed to solve these issues. Density not only ensures the validity of the patterns as well as a channel out time interims with few records which cause overestimating the timespans.

The density of a time interval is calculated as follows:

$$\text{Average transaction per BTC} = \frac{N}{N_{BTCs}} \qquad (3)$$

$$\text{Density} = \alpha \times A \qquad (4)$$

where N is the all-out number of records or transactions, N_{BTCs} is the quantity of fundamental time cubes, therefore, A is the average transaction per BTC. α is called density rate Here we are dynamically generating α value which is introduced to determine the desired density using the equation. If the transcations are more then density rate can be decreased and if it is less, then it can be increased. In this manner, itemset is frequent if and only if for every TC, it fulfils the accompanying condition.

1) $M \overset{Cube}{\Longrightarrow} N$ has support greater than or equal to the minimum threshold which is dynamically generated.
2) To ensure the validity of the rules the time interval (cube) must be dense.

Use apriori like way to find frequent itemsets in different time intervals. If an itemset M is frequent in a time interval.

1) In that time interval all subsets of M are frequent.
2) Frequent itemset M is present in all subsets of interval.

Utilize these properties to develop an algorithm to find frequent itemsets in the transactional database. For mining frequent itemset on temporal data, it requires data with time-related information. The framework uses frequent itemset mining using time cube algorithm. The time cube algorithm is explained below:

The System uses online retail dataset as a database (C). Algorithm for Frequent Itemset Mining with Time Cubes (TCs) steps are shown below in algorithm 1. In the first step of the algorithm is uploading the database and apply preprocessing on that data. The output of the first step is pre-processed data. In third step whole pre-processed data is partitioned into number of parts. In fourth step partition database with time interval using basic time cube (BTC) value. It will partition information into number of candidates. Step 5 is used to calculate support count for each candidate.

In step 6 here the minimum support threshold is dynamically generated. After that step 7 will check support. If support is greater than equal to min sup then only support of the itemset is valid. Step 8 is used for calculating density value. In step 9 the density rate α is generated dynamically. Step 10 is used for repeat the procedure from step 5 to 7 for the entire file. Finally, it gives set of frequent itemsets with their time information.

Algorithm 1 Frequent Itemsets Mining using Basic Time Cube (BTCs)

```
Input
Database (C), Min Sup, Min den, BTC value
Output
Set of frequent itemsets
Method
1. Upload the dataset C
2. Apply data preprocessing on C
```

3. The whole pre-processed data is partitioned into number of parts
4. The time cube interval is taken as input by applying user-defined BTC value on C
5. Calculate support count for each candidate
6. Minimum Support Threshold is generated dynamically.
7. If Support(X) ≥ min Sup then Support is valid
8. Calculate Density as a multiplication of an average number of transactions per time interval (A) and density rate α.
9. Density rate α value is generated dynamically
10. Repeat step 5 to 7 until end of the file
11. The output is generated i.e. set of frequent itemsets with the time interval

C. Enhancing Performance of the Algorithm

Finding regular itemsets is tedious on its own. yet mining designs with temporal data makes it even harder to discover an answer in a sensible time. In this way, it appears to be important to improve the exhibition of the calculation. Since density rate and minimum support threshold is user specified parameters in the existing system. But as an enhancement, we are dynamically generating these user specified parameters. This way the performance of algorithm become more effective for mining frequent itemsets.

D. System Architecture

"Fig. 1" describes the system flow. In which it contains the following modules:

1. Uploading the dataset.
2. Preprocessing the data.
3. Partition the data according to time interval defined by user.
4. Calculate the density of each time cube and filter out less than minimum.
5. Calculate the support count.
6. Obtain frequent itemsets.

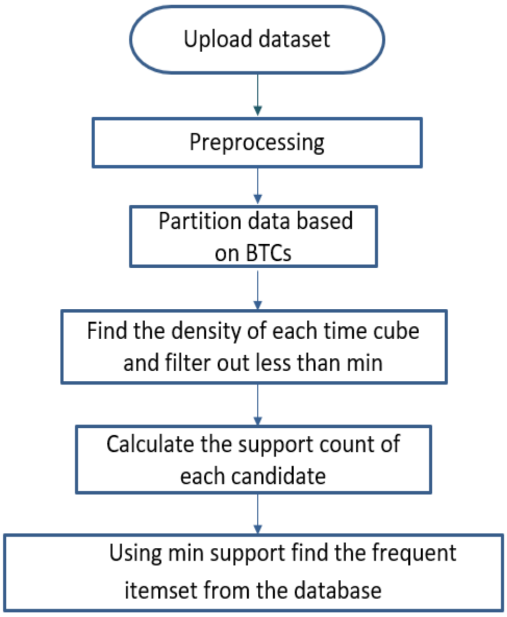

Upload dataset
Preprocessing
Partition data based on BTCs
Find the density of each time cube and filter out less than min
Calculate the support count of each candidate
Using min support find the frequent itemset from the database

Figure 1. System Flow

E. Data Specifications

Performed an experimental study to assess the performance of extended apriori algorithm. The experiment was performed on a computer with an eighth generation 64-bit Core i5 processor running Windows 10, and equipped with 701 GB of free RAM. Performance of the proposed algorithm with partitioning and without partitioning technique are compared by utilizing the given dataset. The experiment was carried out on a transactional information set containing all transactions for a UK-based and registered online retail outlet between 01/12/2010 and 09/12/2011. There are eight attributes in online retail dataset they are Invoice No, Stock Code, Description, Quantity, Invoice Date, Unit Price, Customer ID, Country. These datasets have varied characteristics such as Multivariate, Sequential and Time-Series. This online retail dataset contains 541909 instances. The dataset can be downloaded from (https://archive.ics.uci.edu/ml/datasets/online+retail).

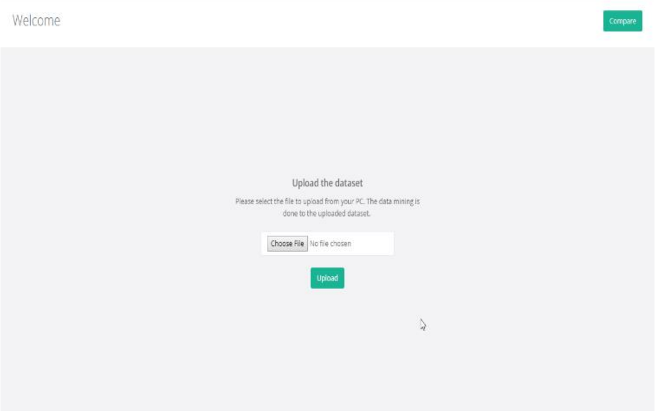
IV. RESULTS AND DISCUSSION

In this section experimental study is finished by way of making use of proposed algorithm. The results of proposed system based on finding frequent itemsets on temporal data and comparison of two techniques, such as partitioning and without partitioning is presented. Here apriori algorithm is extended based on support and density as a new threshold.

The exploratory investigation of the algorithm utilizing online retail dataset demonstrates that frequent itemsets are acquired in a reasonable measure of time where partitioning the whole database makes better results. Here the computation time is less because of partitioning the whole database. Density rate and minimum support threshold is user parameter before, but here it is dynamically generated which will make performance of the algorithm more efficient. The previous research didn't focus on these user specified parameters. Also, analysis done on datasets based on time taken for both partitioning and without partitioning approach. We can see that with partitioning it will give better outcomes as the computation time is less contrasted with without partitioning.

A. Experimental Results

The implementation results can be shown as figure below:

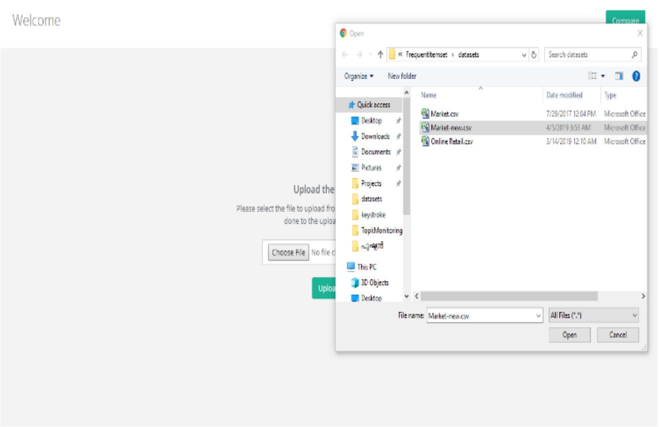


Upload the dataset

Please select the file to upload from your PC. The data mining is done to the uploaded dataset.

Figure 2. Uploading the dataset

"Fig. 2" shows that the dataset file is chosen for uploading.

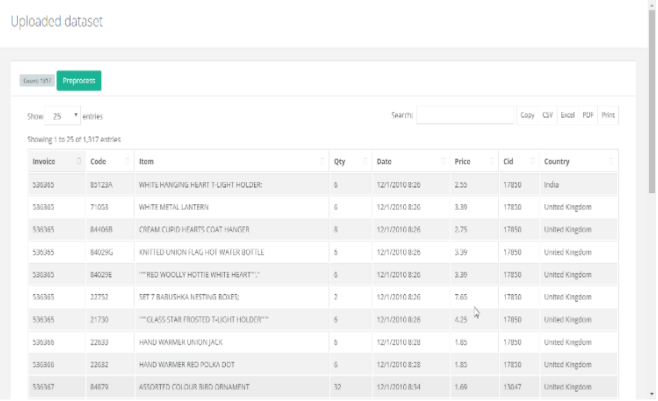


Name	Date modified	Type
Market.csv	7/29/2017 12:04 PM	Microsoft Office
Market-new.csv	4/5/2019 3:53 AM	Microsoft Office
Online Retail.csv	3/14/2019 12:10 AM	Microsoft Office

File name: Market-new.csv

Figure 3. Import the dataset Market-new.csv

"Fig. 3" shows the dataset Market-new.csv is selected and uploaded.

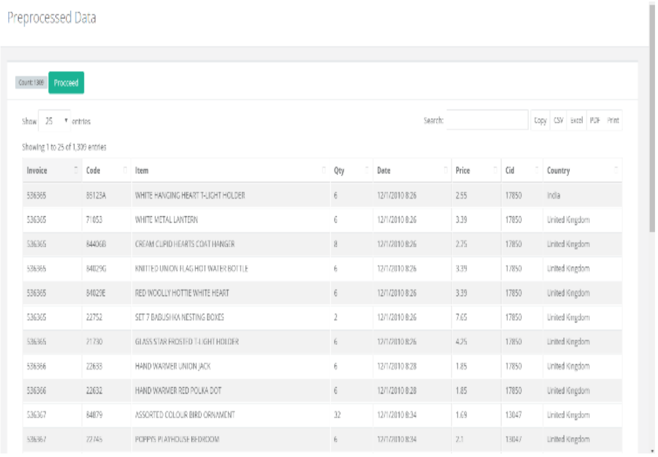


Showing 1 to 25 of 1,317 entries

Invoice	Code	Item	Qty	Date	Price	Cid	Country
536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER:	6	12/1/2010 8:26	2.55	17850	India
536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850	United Kingdom
536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850	United Kingdom
536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850	United Kingdom
536365	84029E	""RED WOOLLY HOTTIE WHITE HEART"".	6	12/1/2010 8:26	3.39	17850	United Kingdom
536365	22752	SET 7 BABUSHKA NESTING BOXES;	2	12/1/2010 8:26	7.65	17850	United Kingdom
536365	21730	""GLASS STAR FROSTED T-LIGHT HOLDER""	6	12/1/2010 8:26	4.25	17850	United Kingdom
536366	22633	HAND WARMER UNION JACK	6	12/1/2010 8:28	1.85	17850	United Kingdom
536366	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 8:28	1.85	17850	United Kingdom
536367	84879	ASSORTED COLOUR BIRD ORNAMENT	32	12/1/2010 8:34	1.69	13047	United Kingdom

Figure 4. Dataset is taken for preprocessing

"Fig. 4" shows Market-new.csv is taken for preprocessing. Check the data's in the database for special characters and remove them. If relevant field in the table data contains null value then remove the entry.



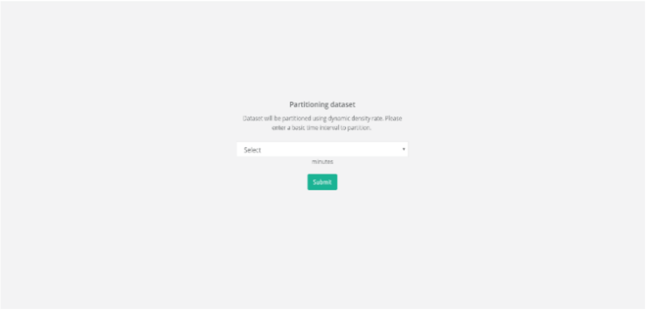
Preprocessed Data

Showing 1 to 25 of 1,309 entries

Invoice	Code	Item	Qty	Date	Price	Cid	Country
536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850	India
536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850	United Kingdom
536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850	United Kingdom
536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850	United Kingdom
536365	84029E	RED WOOLLY HOTTIE WHITE HEART	6	12/1/2010 8:26	3.39	17850	United Kingdom
536365	22752	SET 7 BABUSHKA NESTING BOXES	2	12/1/2010 8:26	7.65	17850	United Kingdom
536365	21730	GLASS STAR FROSTED T-LIGHT HOLDER	6	12/1/2010 8:26	4.25	17850	United Kingdom
536366	22633	HAND WARMER UNION JACK	6	12/1/2010 8:28	1.85	17850	United Kingdom
536366	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 8:28	1.85	17850	United Kingdom
536367	84879	ASSORTED COLOUR BIRD ORNAMENT	32	12/1/2010 8:34	1.69	13047	United Kingdom
536367	22745	POPPY'S PLAYHOUSE BEDROOM	6	12/1/2010 8:34	2.1	13047	United Kingdom

Figure 5. Get the pre-processed data

"Fig. 5" shows that pre-processed data is obtained after removing special characters and null values.

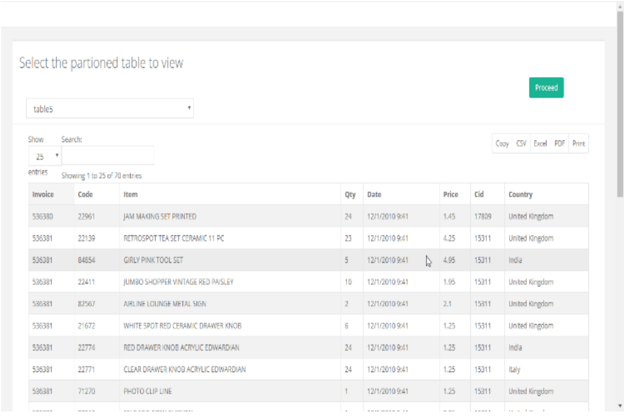


Partitioning dataset

Dataset will be partitioned using dynamic density rate. Please enter a basic time interval to partition.

Figure 6. Partition data according to the given time interval

"Fig 6" shows the data is partitioned according to time interval given by user.



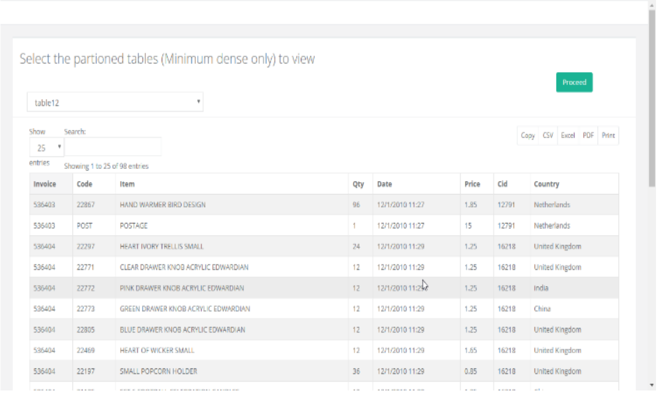
Select the partioned table to view

Showing 1 to 25 of 70 entries

Invoice	Code	Item	Qty	Date	Price	Cid	Country
536380	22961	JAM MAKING SET PRINTED	24	12/1/2010 9:41	1.45	17809	United Kingdom
536381	22139	RETROSPOT TEA SET CERAMIC 11 PC	23	12/1/2010 9:41	4.25	15311	United Kingdom
536381	84854	GIRLY PINK TOOL SET	5	12/1/2010 9:41	4.95	15311	India
536381	22411	JUMBO SHOPPER VINTAGE RED PAISLEY	10	12/1/2010 9:41	1.95	15311	United Kingdom
536381	82567	AIRLINE LOUNGE METAL SIGN	2	12/1/2010 9:41	2.1	15311	United Kingdom
536381	21672	WHITE SPOT RED CERAMIC DRAWER KNOB	6	12/1/2010 9:41	1.25	15311	United Kingdom
536381	22774	RED DRAWER KNOB ACRYLIC EDWARDIAN	24	12/1/2010 9:41	1.25	15311	India
536381	22771	CLEAR DRAWER KNOB ACRYLIC EDWARDIAN	24	12/1/2010 9:41	1.25	15311	Italy
536381	71270	PHOTO CLIP LINE	1	12/1/2010 9:41	1.25	15311	United Kingdom

Figure 7. The partitioned tables are viewed here by selecting each one of them

"fig 7" shows the partitioned tables which was partitioned according to user input. Each partitioned table can be viewed here by selecting each one of them.



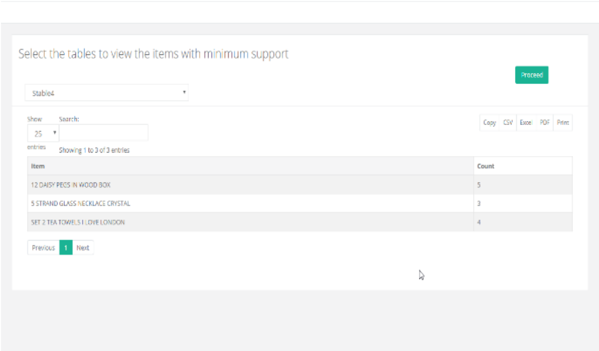
Select the partioned tables (Minimum dense only) to view

Showing 1 to 25 of 98 entries

Invoice	Code	Item	Qty	Date	Price	Cid	Country
536403	22867	HAND WARMER BIRD DESIGN	96	12/1/2010 11:27	1.85	12791	Netherlands
536403	POST	POSTAGE	1	12/1/2010 11:27	15	12791	Netherlands
536404	22297	HEART IVORY TRELLIS SMALL	24	12/1/2010 11:29	1.25	16218	United Kingdom
536404	22771	CLEAR DRAWER KNOB ACRYLIC EDWARDIAN	12	12/1/2010 11:29	1.25	16218	United Kingdom
536404	22772	PINK DRAWER KNOB ACRYLIC EDWARDIAN	12	12/1/2010 11:29	1.25	16218	India
536404	22773	GREEN DRAWER KNOB ACRYLIC EDWARDIAN	12	12/1/2010 11:29	1.25	16218	China
536404	22805	BLUE DRAWER KNOB ACRYLIC EDWARDIAN	12	12/1/2010 11:29	1.25	16218	United Kingdom
536404	22469	HEART OF WICKER SMALL	12	12/1/2010 11:29	1.65	16218	United Kingdom
536404	22197	SMALL POPCORN HOLDER	36	12/1/2010 11:29	0.85	16218	United Kingdom

Figure 8. The partitioned tables are viewed whose records equal or greater than density value

"Fig. 8" shows the density is calculated for each table. If in a time cube, i.e. time interval the density rate is less than minimum density which is dynamically generated, next time cube is checked. Each table can be viewed after filter out the tables which are less than minimum density rate.



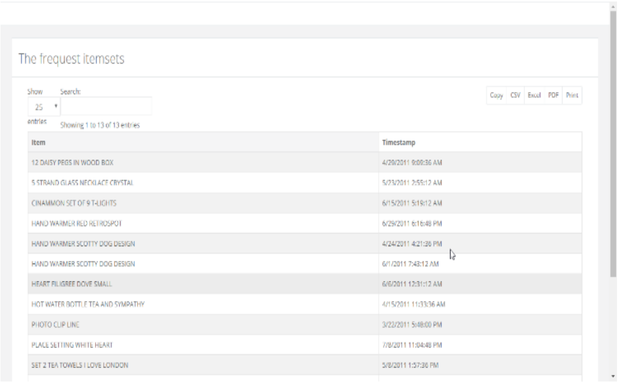
Select the tables to view the items with minimum support

Showing 1 to 3 of 3 entries

Item	Count
12 DAISY PEGS IN WOOD BOX	5
5 STRAND GLASS NECKLACE CRYSTAL	3
SET 2 TEA TOWELS I LOVE LONDON	4

Figure 9. Selecting the tables to view the items with support count greater or equal to minimum support

"Fig. 9" shows the tables after calculating the Support count of each item. If the item has Support count less than minimum support which is also dynamically generated, item is dropped.



The frequest itemsets

Show 25 entries

Search:

Showing 1 to 13 of 13 entries

Item	Timestamp
12 DAISY PEGS IN WOOD BOX	4/29/2011 9:09:36 AM
5 STRAND GLASS NECKLACE CRYSTAL	5/23/2011 2:55:12 AM
CINAMMON SET OF 9 T-LIGHTS	6/15/2011 5:19:12 AM
HAND WARMER RED RETROSPOT	6/29/2011 6:16:48 PM
HAND WARMER SCOTTY DOG DESIGN	4/24/2011 4:21:36 PM
HAND WARMER SCOTTY DOG DESIGN	6/1/2011 7:43:12 AM
HEART FILIGREE DOVE SMALL	6/6/2011 12:31:12 AM
HOT WATER BOTTLE TEA AND SYMPATHY	4/15/2011 11:33:36 AM
PHOTO CLIP LINE	3/22/2011 5:48:00 PM
PLACE SETTING WHITE HEART	7/8/2011 11:04:48 PM
SET 2 TEA TOWELS I LOVE LONDON	5/8/2011 1:57:36 PM

Figure 10. Obtain the frequent itemsets

"fig. 10" shows the frequent itemsets obtained after Partitioning *the* data and calculating the density value and Support of each item.

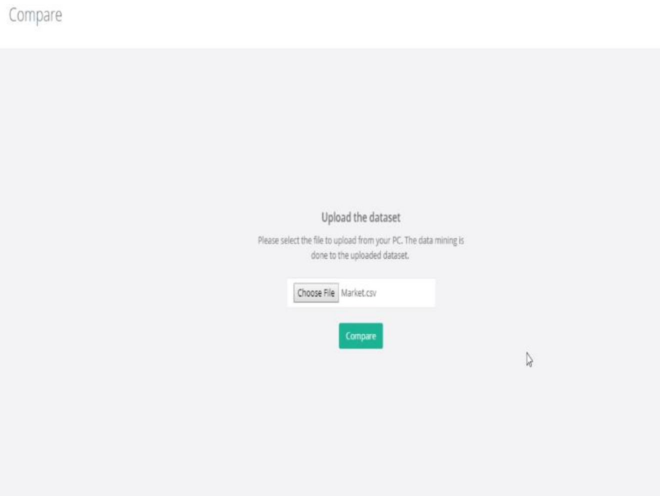
B. Comparison

TABLE I
COMPARISON RESULTS OF PARTITIONING AND WITHOUT PARTITIONING TECHNIQUE DONE ON THE DATASET

Method	**Computational Time**	**Scalability**	**Mining Based on Time Period**
Without Partitioning	High	Low	No
With Partitioning Technique	Medium	High	Yes

Table II above shows the comparison of two methods such as partitioning the data and without partitioning the data is taken for comparison for discovering the efficient strategy for mining frequent itemset on temporal information in a reasonable measure of time. The factors such as computational time, scalability and mining based on time period are taken for comparison. In the case of without partitioning the data, the computational time is high and scalability is low and in this case the mining is not based on time period. We are taking the whole database for discovering frequent itemsets which is inefficient. And in the case of partitioning technique, computation time is medium and scalability is high and also mining is based on time period which is one of the efficient methods for discovering frequent itemsets*.*

The comparison of methods such as partitioning the data and without partitioning the data is done on the dataset. To realize which is the best strategy for frequent itemset mining. When the data is partitioned according to given time interval, it takes less time for computation. But when data is not partitioned, finding frequent itemsets become more complex. So, the algorithm is more effective in the case of using partitioning technique for finding frequent itemsets. If the computation time is less then we can mine frequent itemset effectively. Below "Fig. 11" and "Fig. 12" shows the implementation results of comparison of two methods.



Compare

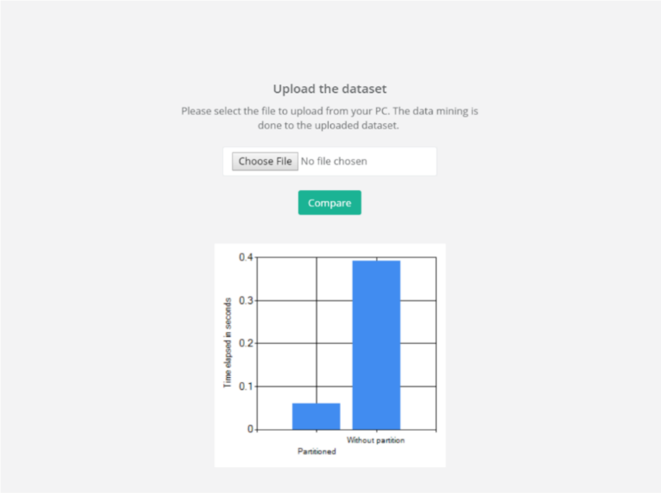
Upload the dataset

Please select the file to upload from your PC. The data mining is done to the uploaded dataset.

Choose File Market.csv

Figure 11. Uploading the dataset Market.csv for comparison

"Fig. 11" shows that the dataset Market.csv is taken for comparison



Upload the dataset

Please select the file to upload from your PC. The data mining is done to the uploaded dataset.

Figure 12. Obtain the graph which shows time taken (in sec) for partitioning and without partitioning data

“Fig. 12” shows the Graph obtained which shows time taken (in sec) after the comparison between the partitioning and without partitioning the data.

V. CONCLUSION

The paper mainly concentrates on developing an efficient algorithm for mining frequent itemset by extending apriori and gives frequent itemset along with time related data as output. And also focuses on limitation of existing system, where density rate and minimum support threshold are given by the user, but in this paper, they are dynamically generated which will make frequent itemset mining more efficient. Also, comparison of two methods such as partitioning and without partitioning technique is done on dataset with respect to time. Partition technique, which shows less computation time is taken when partition is done to dataset than without partitioning. So, calculation time is less in mining frequent itemsets when partition procedure is utilized. For future work, enhance performance of the algorithm by using multithreaded processors such as graphic processing units to speed up the computations.

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Cite this article as :

Fathima Sherin T K, Anish Kumar B., "An Efficient Method for Frequent Itemset Mining on Temporal Data", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 5 Issue 3, pp. 558-568, May-June 2019. Available at doi : https://doi.org/10.32628/CSEIT1953162
Journal URL : http://ijsrcseit.com/CSEIT1953162