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Disk Resident Taxonomy Mining for Large Temporal Datasets

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Abstract

Mining patterns under constraints in large data is a significant task to advantage from the multiple uses of the patterns embedded in these data sets. It is obviously a difficult task because of the exponential growth of the search space. Extracting the patterns under various kinds of constraints in such type of data is a challenging research. First, a memory-based, efficient pattern-growth algorithm, Forest Mine, is proposed for mining frequent patterns for the data sets and then consolidating global frequent patterns. For dense data sets, Forest-mine is integrated with FP-Tree dynamically by detecting the swapping condition and constructing FP-trees for efficient mining. Such efforts ensure that forest mine is scalable in both large and medium sized databases and in both sparse and dense data sets.

Index Terms: *Frequent Generalized Item Set, FP-Tree,Forest Mine, Disk Resident Data structure*

Introduction

Mining frequent data sets is a common problem for mining association rules. It also plays an important role in many data mining tasks like sequential patterns, episodes, multi-dimensional patterns and so on. The description of the problem is as follows. Let $I = \{i_1, i_2, \ldots, i_n\}$, be a set of *items*. Items will sometimes also be denoted by *a, b, c, ...* An *I-transaction* τ is a subset of *I*. An *I*-transactional *database D* is a finite bag of *I*-transactions. The *support* of an itemset $S \subseteq I$ is the proportion of transactions in *D* that contain *S*. The task of mining frequent itemsets is to find all *S* such that the support of *S* is greater than some given *minimum support* ξ, where ξ either is a fraction , or an absolute count. Most of the algorithms, such as Apriori, DepthProject, and dEclat work well when the main memory is big enough to fit the whole database or/and the data structures (candidate sets, FP-trees, etc) [1]. When a database is very large or when the minimum support is very low, either the data structures used by the algorithms may not be accommodated in main memory, or the algorithms spend too much time on multiple passes over the database. In the *First IEEE ICDM Workshop on Frequent Itemset Mining Implementations, FIMI '03*, many well known algorithms were implemented and independently tested. The results show that "*none* of the algorithms is able to gracefully scale-up to very large datasets, with millions of transactions"[1].

At the same time very large databases do exist in real life. In a medium sized business or in a company big as Walmart, it's very easy to collect a few gigabytes of data. Terabytes of raw data are ubiquitously being recorded in commerce, science and government. The question of how to handle these databases is still one of the most difficult problems in data mining[2].

In the paper [1] authors considered the problem of mining frequent itemsets from *very* large databases. They adopt a divide-and-conquer approach. First they presented three algorithms, the general divide-and-conquer algorithm, then an algorithm using basic projection (division), and an algorithm using aggressive projection. They also analyzed the disk I/O's required by those algorithms. In a detailed divide-and-conquer algorithm, called *Diskmine*, they use the highly efficient *FPgrowth** method to mine frequent itemsets from an FP-tree for the main memory part of data mining. We describe several novel techniques useful in mining frequent itemsets from disks, such as the *FP-array* technique, and the *item-grouping* technique.

Existing System

There have been many algorithms developed for fast mining of frequent patterns, which can be classified into two categories. The first category, candidate generation and test approach, such as Apriori as well as many subsequent studies, are directly based on an anti-monotone Apriori property if a pattern with k items is not frequent, any of its super-pattern with (k+1) or more items can never be frequent[3].

Limitations of Existing Systems

1. First, huge space is required to serve the mining. An Apriori-like algorithm generates a huge number of candidates for long or dense patterns
2. Second, real databases contain all the cases.

Real data sets can be sparse and/or dense in different applications

3. Third, large applications need more scalability. Many existing methods are efficient when the data set is not very large. Otherwise, their core data structures (such as FP-tree) or the intermediate results (e.g., the set of candidates in Apriori or the recursively generated conditional databases in FP-growth) may not fit in main memory and easily cause thrashing

Problem Statement

The problem of frequent pattern mining is to find the complete set of frequent patterns in a given transaction database with respect to a given support threshold

Proposed Work

This study is proposing a forest data structure, and a mining algorithm, Forest-mine, which takes advantage of this data structure and dynamically adjusts links in the mining process. A divergent feature of proposed method is that it has very restricted and precisely banal space overhead and runs truly rapid in memory-based setting. Moreover, it can be extended up to very large databases by database segregation, and when the data set becomes impenetrable, FP-trees can be built dynamically in the mining.Tackle the problems of mining in dynamic large data base. This is a challenging task that requires extending disc resident FP-Tree into a dynamic structure that could smoothly absorb modifications to the database.

Mining from disk:

How should one go about when mining frequent item-sets from very large databases residing in a secondary memory storage, such as disks? Here "very large" means that the data structures constructed from the database for mining frequent item-sets can not fit in the available main memory. One approach is *sampling*.. Unfortunately, the results of sampling are probabilistic; some critical frequent item-sets could be missing. Besides the sampling, there are basically two strategies for mining frequent item-sets, the data structures approach, and the divide-and-conquer approach. The *data structures* approach consists of reading the database buffer by buffer, and generates data structures (i.e. Candidate sets or FP-trees). Since the data structure do not fit into primary memory, supplementary disk I/O's are required. The number of passes and disk I/O's required by the approach depends on the algorithm and its data structures.

For examples, if the algorithm is Apriori using a hash-tree for candidate itemsets, disk based hash-trees have to be used. If the algorithm is FP-growth method, as suggested, FP-trees have to be written to the disk. Then the number of disk I/O's for the trees depends on the size of the trees on disk. Note that the size of the trees could be the same as or even bigger than the size of the database. The basic strategy for the *divide-and-conquer* approach is shown in the procedure *diskmine*. In the approach, $|D|$ denotes the size of the data structures used by the mining algorithm, and M is the size of available main memory. After all small databases are processed, all candidate frequent itemsets are combined in some way (obviously depending on the way the decomposition was done) to get all frequent itemsets for the original database.

Procedure *diskmine*(D,M) **if** $|D| \leq M$ **then return** *mainmine(D)* **else** decompose D into $D_1, . . .D_k$. **return** *combine diskmine*(D_1,M),.... , *diskmine*(D_k,M). The efficiency of *diskmine* depends on the method used for mining frequent itemsets in main memory and on the number of disk I/O's needed in the decomposition and combination phases. Sometimes the disk I/O is the main factor. Since the decomposition step involves I/O, ideally the number of recursive calls should be kept small. The faster we can obtain small decomposed databases, the fewer recursive call we will need. On the other hand, if a decomposition cuts down the size of the projected databases drastically, the trade-off might be that the combination step becomes more complicated and might involve heavy disk I/O. In the following we discuss two decomposition strategies, namely decomposition by partition, and decomposition by projection. *Partitioning* is an approach in which a large database is decomposed into cells of small non-overlapping databases. The cell-size is chosen so that all frequent itemsets in a cell can be mined without having to store any data structures in secondary memory. However, since a cell only contains partial frequency information of the original database, all frequent itemsets from the cell are local to that cell of the partition, and could only be *candidate* frequent itemsets, for the intact dataset. Thus the contestant frequent itemsets mined from a unit have to be demonstrated later to filter out false hits. Consequently, those candidate sets have to be written to disk in order to leave space for processing the next cell of the partition.

After generating candidate frequent itemsets from all cells, another database scan is needed to filter out all infrequent itemsets. The segregation approach therefore needs only two passes over the dataset, but inscription and interpretation candidate frequent itemsets will involve a momentous number of disk I/O's, depending on the range of the set of contestant frequent itemsets. To get an easier amalgamation segment, this paper espouses another putrefaction stratagem, which we call *bulge*. This approach projects the imaginative dataset on several databases, each resolute by one or more frequent item(s). One advantage of this approach is that any frequent item set mined from a anticipated database is a frequent itemset in the imaginative database. To get *all* frequent item sets, only need to take the unification of the frequent item sets discovered in the small anticipated databases. The biggest problem of the bulge approach is that the total size of the projected dataset could be excessively large, and there could be excessively many disk I/O's for the projected datasets. Thus, there is a tradeoff between the easier amalgamation segment and possible excessive many disk I/O's. To analyze the recurrence and required disk I/O's of the general divide-and-conquer algorithm when the putrefaction stratagem is projection.

Definition 1 Let I be a set of items. By $I*$ we will enote *strings* over I, such that each symbol occurs at most once in the string. If α, β are strings, then $\alpha.\beta$ denotes the concatenation of the string α with the string β. Let D be an I-database. Then $FI(D)$ is the string over I, such that each frequent item in D occurs in it precisely once, and the items are in non-increasing order of frequency in D. As an example, consider the $\{a, b, c, d, e\}$-database $D = \{\{a, c, d\}, \{b, c, d, e\}, \{a, b\}, \{a, c\}\}$. If the minimum support is 50%, then $freqstring(D) = acbd$.

Definition 2 Let D be an I-database, and let $FI(D) = i_1 i_2 \cdot \cdot \cdot i_k$. For $j \in \{1, . . . , k\}$ we define $Dij = \{\tau \cap \{i_1, . . . , i_j\} : i_j \in \tau, \tau \in D\}$. Let $\alpha \in I*$. We define $D\alpha$ inductively: $D' = D$, and let $FI(D\alpha) = i_1 i_2 \cdot \cdot \cdot i_k$. Then, for $j \in \{1, . . . , k\}$, $D\alpha.ij = \{\tau \cap \{i_1, . . . , i_j\} : i_j \in \tau, \tau \in D\alpha\}$. Obviously, $D\alpha.i_j$ is an $\{i_1, . . . , i_j\}$ -database. The putrefaction of $D\alpha$ into $D\alpha.i_1, . . . , D\alpha.i_k$ is called the *basic estimate*. To illustrate the basic estimate, from earlier example, starting from the least frequent item in the *FI*, one can obtain $Dd = \{\{a, c, d\}, \{b, c, d\}\}$, $Db = \{\{c, b\}, \{a, b\}\}$, $Dc = \{\{a, c\}, \{c\}, \{a, c\}\}$, and $Da = \{\{a\}, \{a\}, \{a\}\}$.

Definition 3 Let $\alpha \in I*$, $i_j \in I$, and let $D\alpha.i_j$ be an I database. Then $FS(\xi, D\alpha. i_j)$ denotes the subsets of I that contain i_j and are frequent in $D\alpha. i_j$ when the minimum support is ξ. Usually, we shall abstract ξ away, and write just $FS(D\alpha. i_j)$.

In the previous example, for D_d, $FS(D_d)=\{\{d\}, \{c, d\}\}$. Note though $\{c\}$ is also frequent in D_d, it is not listed since it does not contain d. It will be listed in $FS(D_c)$. Similarly, $FS(D_b)=\{\{b\}\}$, $FS(D_c)=\{\{c\}, \{a, c\}\}$ and $FS(D_a)=\{\{a\}\}$. We also can notice that D_d and D_c are not that much smaller than the original database. The upside is though that the set of all frequent itemsets in D now simply is the union of $FS(D_d)$, $FS(D_b)$, $FS(D_c)$ and $FS(D_d)$. This means that the combination phase is a simple union. The following procedure *BDM* gives a divide-and-conquer algorithm that uses basic projection. A transaction τ in $D\alpha$ will be partly inserted into $D\alpha. i_j$ if and only if τ contains i_j . The parallel projection algorithm introduced an algorithm of this kind.

```
**Procedure** BDM(Dα,M)
**if** |Dα| ≤ M **then return** mainmine( Dα)
**else** let FI(Dα) = i_1 i_2 · · · i_n,
**return** DISKMINE(Dα. i_1,M) ∪ . . . ∪ BDM(Dα. i_n,M).
```

Let's analyze the disk I/O's of the algorithm *BDM*. As before, we assume that there are two passes, that the data structure is an FP-tree, and that the main memory mining method is *FP-growth*. If in D', each transaction contains on the average n frequent items, each transaction will be written to n projected databases. Thus the total length of the associated transactions in the projected databases is $n+(n-1)+ \cdot \cdot \cdot +1 = n(n+1)/2$, the total size of all projected databases is $(n+1)/2 \cdot D \approx n/2 \cdot D$. Still there are two full database scans and a incomplete database scan for D', as explained for formula (1). The number of total disk I/O's is $5/2 \cdot D/B$. The projected databases have to be written to the disks first, then later scanned twice each for building an FP-tree. This step needs at least $3 \cdot n/2 \times D/B$. Thus, the total disk I/O's for the divide-and-conquer algorithm with basic projection is $5/2 \cdot D/B + n \cdot 3/2 \cdot D/B$ (2) The recurrence structure of *BDM* is shown in Figure 1. The reader should ignore nodes in the shaded area at this point, they represent processing in main memory.

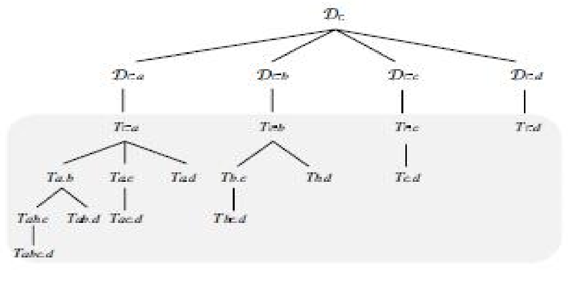


Figure 1 Recurrence of Basic Projection

In a typical application *n*, the average number of frequent items could be hundreds, or thousands. It therefore makes sense to devise a smarter projection strategy. Before we go further, we introduce some definitions and a lemma.

Generalized Itemset Discovery: The rules that are generated by support and confidence are difficult to analyse which is called Association rule extraction, even if their buried data might be relevant. To analyse similarities between data's are done by powerful and effective tools where even some buried information are extracted by previous approaches. The objective is to monitor tactic that balance the data immoderation load and better utilize a multi-core cluster system for data mining application. The main issue in this paper is low performance. It won't mine all frequent generalizations of an atypical pattern, but slightly generates only the one characterized by low redundancy

2) Change Detection in Datasets: This paper presents a sketch out to detect changes inside a data set at imaginary level very deeply. The main idea is to obtain a rule-based illustration of the data set at different time period and to rarely analyze how these regulations change. Discovering changes and acting upon to or them or before any other item-set others has become a tenaciously issue for many organization. Prevailing data analysis practices shows that task under contemplation is steady over number of times due to conjecture. Here exposure and mutable are made at imaginary level only it may not be real or true. The main shortcoming is conferred previously. Pretend may sometimes workout but not all the time. The detection, based on real dataset should be made to get accurate result

3) Frequent Generalized Item Sets: FGIS takes input as pecking order. Then classify it and harvests generalized item-set by using association rules which happens same in generalized item-set. The results generated by using association rules are strongly recommended by users not automatically generated. The FGIS algorithm amends and conglomerates result produced by two algorithms. The result encloses unordered item-sets. These algorithms extract item-set by processing transactional database. FGIS+ The shortcoming in FGIS is recovered by FGIS+. It is proficient and solves numerous problems of pattern extraction, such as the expensive creation of Training date set sets and the over-generalization of rules. Item set parallelism in multiprocessing and multi-computing state is analyzed in this paper. Another important drawback isload balancing, this is also recovered. But the drawback in FGIS + is dynamic load balancing where both candidate set and computation task are handled.

Load Items

The Load items will load the items from the database for the mining task is to discover a set of attributes shared among a large number of objects in a given database.

Load Transaction

This transactional database, first scan the database once to collect the count of the items present in the database. Then, sort the items according to their frequencies in descending order to build the frequent item list. Only items those come across the minimum support threshold are deliberated for building the FP-tree. All items are carried out with their support counts.

Load next window

It performs a second scan of the transactional database to build the FP-tree. Begin with an empty root and add the transactions one-by-one as prefix subtrees of the root. After reading each transaction, sort its items in descendant order by the support.

Build Tree

This subunit builds in memory the initial FP-tree from the raw data files. The transactions are read from the file one-by-one; and they are added to the tree which is realized in the FP-nodes-list. Management of the FP-nodes-list is done by MMU which keeps track of the free and already occupied nodes of the list. While constructing the FP-tree in M.B, this subunit may consult the tree translation unit of MMU in order to translate part of the current tree into secondary storage system S; this will make room for the new FP-nodes corresponding to the transactions to be added next. After the translation process, the tree construction will resume to use FP-nodes by assuming that no part of the tree is present in main memory. Here, it is worth mentioning that the effect of this tree translation process will lead to the situation as if the initial tree has been constructed as separate chunks of trees. Consequently, the complete set of truncated transactions of the database will be represented by these chunks of trees and the mining result will not be affected. However, the database will not be as compressed as the original FP-tree because multiple paths sharing same prefix

SaveTree

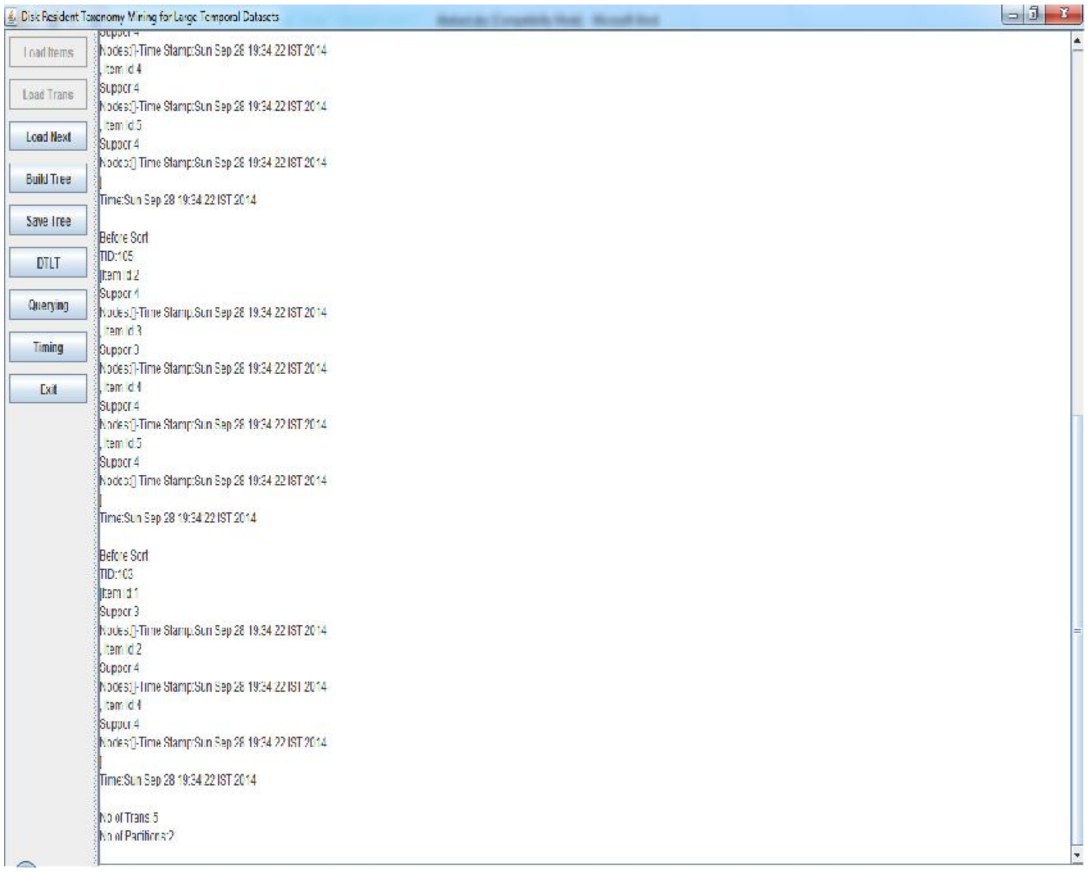
The 'Build Tree from the Database' subunit, it may find that there is not enough space available in 'FP-Nodes list' to continue the tree building process and may consequently decide to save the current base tree or one of the conditional FP-trees in the secondary storage system. If the current base tree is rendered onto disc, the afresh added I/O- cognizant prefix-tree blocks are marked and the item for which the last conditional FP-tree has been built is saved into the lastTree variable. As the current base tree is no longer in memory in this case, the algorithm ceases processing the memory-based portion of the tree by breaking out of the loop. We require the lastTree variable because this memorizes the point at which we break out from the loop. For items with ids > lastTree, we still need to traverse that portion of the base tree which was just saved in the secondary storage

DTLT Structure

Disc Tree Location Table (DTLT) is an R-tree based structure that stores the knowledge of Prefix-Treediscnode-Id ranges associated with each prefix-tree in order to facilitate easy lookups of the blocks that constitute a particular Prefix-Treedisc as a disc file. The DTLT structure gets affected when the tree translation unit translates some of the FP-trees from memory to I/O-conscious prefix-trees, which are all represented in a single file-based structure. At any stage of the mining process, multiple FP-trees might be available in memory. The mining model may need to make room in the available memory

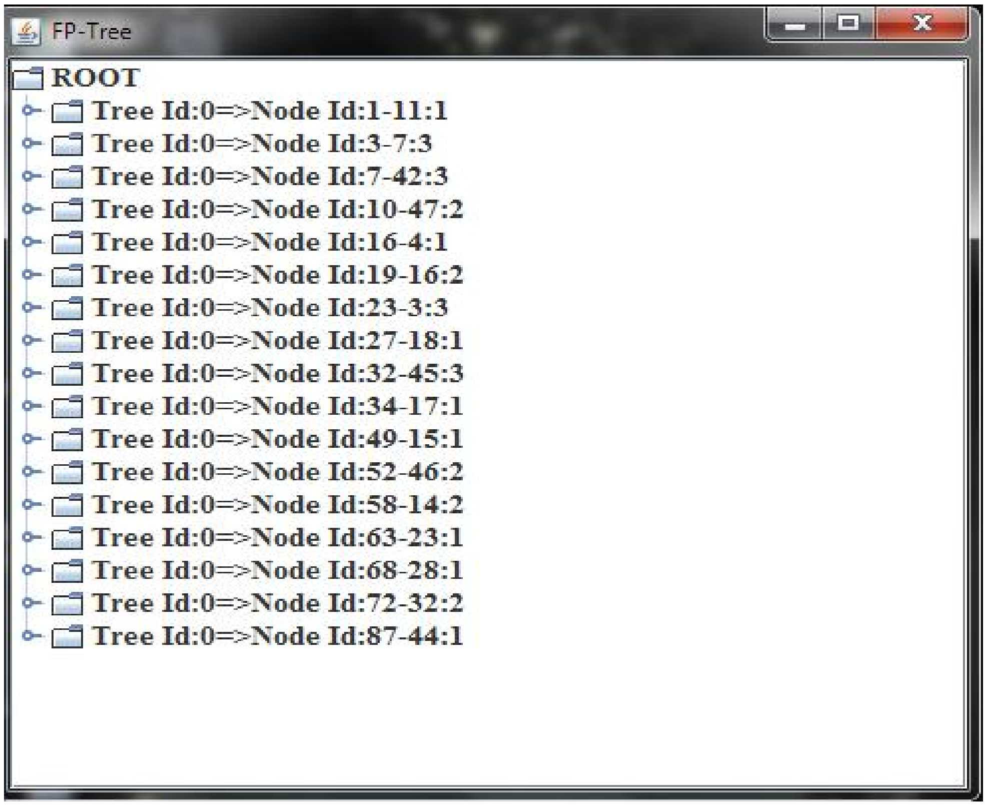
space M.B by translating some of the FP-trees into disc-based I/O-conscious prefix-trees; this is realized in multiple blocks, where each block size is less that the size of FB in order to be accommodated in FB at a later stage. Subsequently, the mining model also inserts block location data for a particular prefix-tree into DTLT structure

Results



```
Nodes:[]-Time Stamp:Sun Sep 28 19:34:22 IST 2014
, Item id:4
Suppor:4
Nodes:[]-Time Stamp:Sun Sep 28 19:34:22 IST 2014
, Item id:5
Suppor:4
Nodes:[] Time Stamp:Sun Sep 28 19:34:22 IST 2014
]
Time:Sun Sep 28 19:34:22 IST 2014

Before Sort
TID:105
[Item id:2
Suppor:4
Nodes:[]-Time Stamp:Sun Sep 28 19:34:22 IST 2014
, Item id:3
Suppor:3
Nodes:[]-Time Stamp:Sun Sep 28 19:34:22 IST 2014
, Item id:4
Suppor:4
Nodes:[]-Time Stamp:Sun Sep 28 19:34:22 IST 2014
, Item id:5
Suppor:4
Nodes:[] Time Stamp:Sun Sep 28 19:34:22 IST 2014
]
Time:Sun Sep 28 19:34:22 IST 2014

Before Sort
TID:103
[Item id:1
Suppor:3
Nodes:[]-Time Stamp:Sun Sep 28 19:34:22 IST 2014
, Item id:2
Suppor:4
Nodes:[]-Time Stamp:Sun Sep 28 19:34:22 IST 2014
, Item id:4
Suppor:4
Nodes:[]-Time Stamp:Sun Sep 28 19:34:22 IST 2014
]
Time:Sun Sep 28 19:34:22 IST 2014

No of Trans:5
No of Paritions:2
```

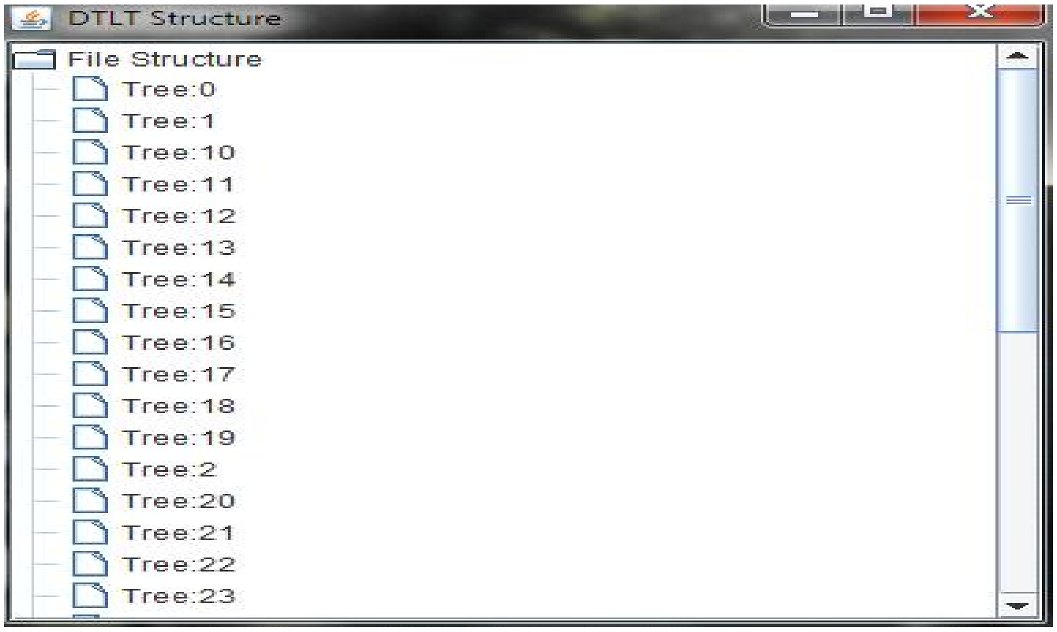
Figure 2 After Transaction Loading



FP-Tree

```
ROOT
  Tree Id:0=>Node Id:1-11:1
  Tree Id:0=>Node Id:3-7:3
  Tree Id:0=>Node Id:7-42:3
  Tree Id:0=>Node Id:10-47:2
  Tree Id:0=>Node Id:16-4:1
  Tree Id:0=>Node Id:19-16:2
  Tree Id:0=>Node Id:23-3:3
  Tree Id:0=>Node Id:27-18:1
  Tree Id:0=>Node Id:32-45:3
  Tree Id:0=>Node Id:34-17:1
  Tree Id:0=>Node Id:49-15:1
  Tree Id:0=>Node Id:52-46:2
  Tree Id:0=>Node Id:58-14:2
  Tree Id:0=>Node Id:63-23:1
  Tree Id:0=>Node Id:68-28:1
  Tree Id:0=>Node Id:72-32:2
  Tree Id:0=>Node Id:87-44:1
```

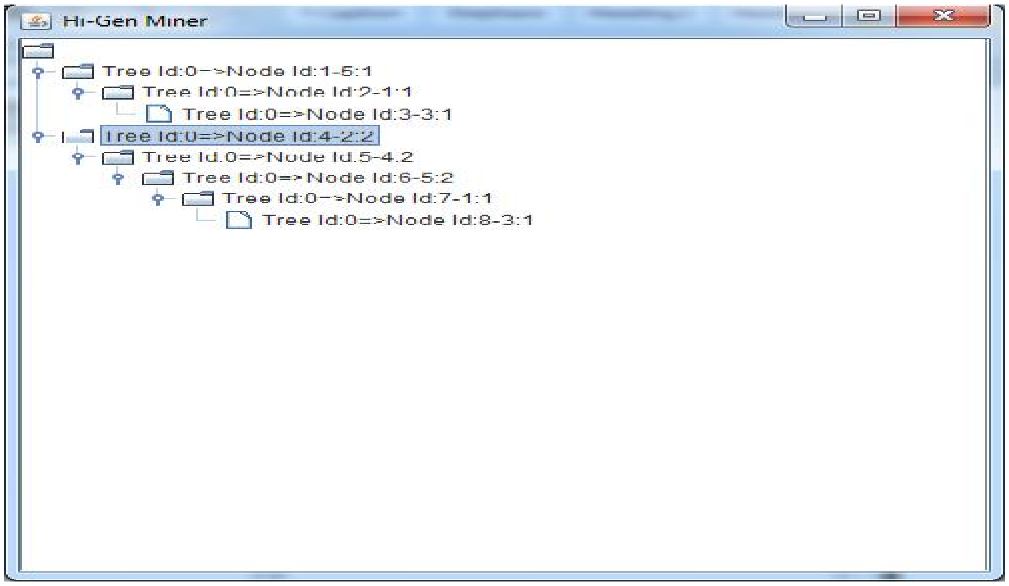
Figure 3 Tree Structure



DTLT Structure

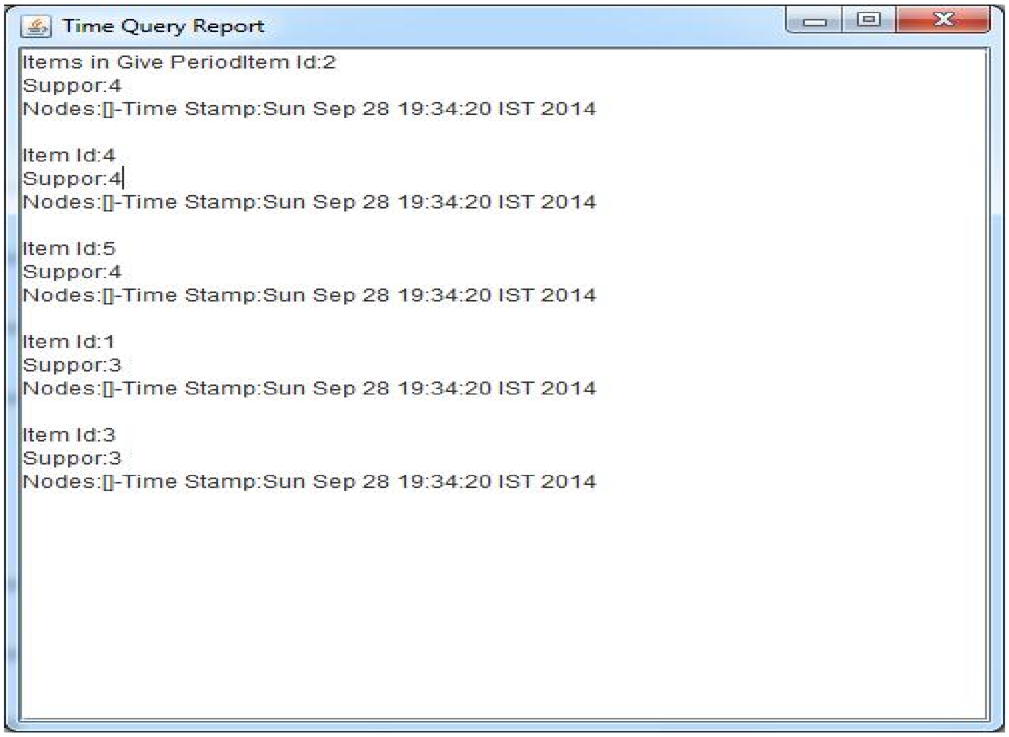
```
File Structure
  Tree:0
  Tree:1
  Tree:10
  Tree:11
  Tree:12
  Tree:13
  Tree:14
  Tree:15
  Tree:16
  Tree:17
  Tree:18
  Tree:19
  Tree:2
  Tree:20
  Tree:21
  Tree:22
  Tree:23
```

Figure 4 HiGen Disk Resident Tree Model



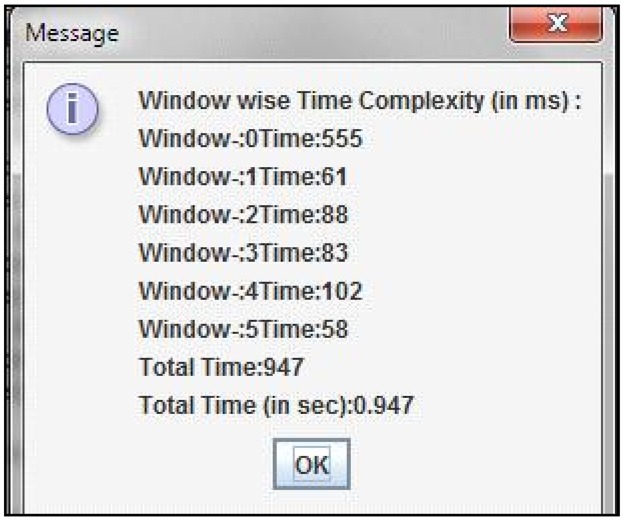
```
Tree Id:0=>Node Id:1-5:1
  Tree Id:0=>Node Id:2-1:1
    Tree Id:0=>Node Id:3-3:1
Tree Id:0=>Node Id:4-2:2
  Tree Id:0=>Node Id:5-4:2
    Tree Id:0=>Node Id:6-5:2
      Tree Id:0=>Node Id:7-1:1
        Tree Id:0=>Node Id:8-3:1
```

Figure 5 Auxiliary HiGen Miner



```
Items in Give PeriodItem Id:2
Suppor:4
Nodes:[]-Time Stamp:Sun Sep 28 19:34:20 IST 2014

Item Id:4
Suppor:4
Nodes:[]-Time Stamp:Sun Sep 28 19:34:20 IST 2014

Item Id:5
Suppor:4
Nodes:[]-Time Stamp:Sun Sep 28 19:34:20 IST 2014

Item Id:1
Suppor:3
Nodes:[]-Time Stamp:Sun Sep 28 19:34:20 IST 2014

Item Id:3
Suppor:3
Nodes:[]-Time Stamp:Sun Sep 28 19:34:20 IST 2014
```

Figure 6 Temporal Query



```
Window wise Time Complexity (in ms) :
Window-:0Time:555
Window-:1Time:61
Window-:2Time:88
Window-:3Time:83
Window-:4Time:102
Window-:5Time:58
Total Time:947
Total Time (in sec):0.947
```

Figure 7 Time Complexity

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