Abstract—In real world applications, most transaction databases are often large and constantly updated. Current data mining algorithms face the problem of processing a large number of transactions in dynamic environments. Since memory space is limited, it is critical to be able to use available storage efficiently and to process more transactions. In this paper, we propose an improved data structure of a compressed FP-tree to mine frequent itemsets with greater efficiency. Use of our method can minimize the I/O overhead, and, more importantly, it can also perform incremental mining without rescanning the original database. Our experimental results show that the method we propose not only requires less memory, but also performs incremental mining more efficiently.

Index Terms—Association rule, Frequent pattern, Compressed FP-tree, Incremental data mining

I. INTRODUCTION

In data mining research, transaction databases are often large and constantly updated. This causes problems for many data mining algorithms [1-2] since the available memory space is limited. Apart from the storage problem, processing the transaction database incrementally in an efficient manner is also a critical issue. Traditional data mining approaches recalculate the whole database after updates are made, but it is not efficient to repeat the same process more than once. Therefore, it is necessary to develop data mining algorithms that can both process dynamic databases [3-6] using a better method and utilize memory space more efficiently.

Traditional data mining algorithms generate many candidates to find frequent itemsets like the Apriori algorithm [1]. In addition to the problem of the large number of candidates, this algorithm also demands an efficient data structure to store frequent itemsets for further processing. Without needing to generate all candidates, FP-growth [2], fully utilizes the common path of the FP-tree structure to store potential frequent itemsets. However, this is not optimal for the incremental mining of dynamic databases. FP-growth scans the database and sorts the frequent items by their frequencies. Since the updated database likely causes the frequent item sequences to change, FP-tree must be rebuilt such that frequent itemsets can be identified accordingly.

Our challenge is to improve the storage of potential frequent itemsets for incremental mining while retaining the advantage of sharing the common path of FP-tree. In this paper, we propose a compact structure for storing potential frequent itemsets based on FP-tree to process item transactions in main memory.

In addition, transaction databases are updated regularly in real world situations. In most cases, FP-growth must rescan the updated database and rebuild FP-tree, due to the change in the support count of frequent 1-itemsets. To avoid the cost of repeatedly scanning the original database, we simply adjust, rather than completely rebuild, the tree after the updating process. Since we can compress the FP-tree structure to save storage space, we can build a compact version of FP-tree without specifying the minimum support. Therefore, our approach allows incremental mining of dynamic databases for any support threshold.

II. RELATED WORK

Association rule mining [7-10] is one of the most popular data mining techniques. It finds interesting information among a large set of data items which appear together. For example, the rules found from a sales database are useful for the marketing manager’s decision making. The application of these association rules is in market basket analysis. This mining helps the decision maker analyze customers’ purchasing habits by discovering association among items.

Han et al. proposed the FP-growth [2] algorithm to mine frequent itemsets without generating candidate itemsets. FP-growth uses a tree structure, FP-tree, to
solve the problem of Apriori for efficiently mining association rules. FP-tree captures the content of the transaction database and compresses all the transactions. It successfully avoids scanning the database many times.

In addition to FP-tree, a header table is used to traverse the tree and find frequent itemsets quickly. The header records frequent 1-itemsets in decreasing order of their frequencies. Each 1-itemset in the header table points to the corresponding node of FP-tree. If two nodes of FP-tree have the same item, a link will be generated between them. During construction an FP-tree needs to scan the transaction database twice.

The next part of the FP-growing algorithm is to mine frequent patterns using the constructed FP-tree. It traverses the nodes of frequent itemsets from the least frequent item to the root of the FP-tree by using the header table. Paths with the same prefix item in the FP-tree are used to construct the conditional FP-tree. Using the conditional FP-tree, the algorithm can generate frequent itemsets with the same prefix.

FIU-tree [11] was proposed to use a special frequent items ultrametric tree, called FIU-tree. The algorithm puts frequent k-itemsets into FIU-tree. These items are stored in the tree by lexicographical order to compress the items for more efficient use of memory space. This algorithm only scans the database twice. It can be divided into two phases. In the first phase, it scans the database to generate all frequent items and prune infrequent items. Next, frequent items are stored in lexicographical order. In the second phase, the algorithm constructs a frequent items ultrametric tree, i.e., FIU-tree, for mining frequent itemsets.

[12-14] use a compressed FP-tree approach to reduce the number of nodes. However, they cannot deal with transaction updates or the change in the support count threshold.

III. PROPOSED METHOD

In this section, we describe our proposed approach and introduce how it works. Simple examples will then be presented in the next section.

A. Basic Concept of Our Approach

Although traditional FP-growth employs the compact structure of FP-tree by taking advantage of the common prefix, it still cannot work for very large databases. To deal with the space problem, we try to further compress the nodes in the FP-tree. Therefore, we propose a compressed version of the FP-tree, called CFP-tree. Items with the same count value will be put into the same node.

In addition, FP-growth is not suitable for incremental data mining. Because an FP-tree is based on the set of frequent items, it needs to be re-built when the database updates change them. A more serious problem is the dynamic of the data mining application where the support thresholds vary constantly. Since in most cases a different support threshold would result in a different set of frequent items, FP-Tree needs to re-scan the database to build a new FP-tree. Since FIUT suffers similar problems, no further discussion of this will be made. To enable incremental data mining with varying support thresholds, we build FP-tree with all the items in the database.

Thus, we propose a compressed version of the FP-tree, called CFP-tree, to improve the usage of memory space. Instead of re-building FP-tree after the database updates and/or support threshold changes, we dynamically adjust the FP-tree which is built with all the items in the database.

B. Our Proposed Algorithm

We propose an algorithm called ADMiner that uses an assemble-and-detach approach for mining incremental datasets. We define some terms and symbols as below:

Definition 1. Let $P=\{i_1,i_2,...,i_n\}$ be a set of distinct items and $T=\{t_1,t_2,...,t_m\}$ be a set of transaction identifiers. A database DB contains a set of transactions in the form of $\langle\text{tid, itemset}\rangle$ where $\text{tid}$ and itemset$\subseteq P$.

Definition 2. Let $X$ be an itemset where $X\subseteq I$. We say that $X$ is a frequent itemset (pattern) if the frequency of $X$ appearing in the transactions of a DB is greater than or equal to a user specified threshold (min-sup).

Definition 3. Let $i,j$ be two items with frequencies $f_i$ and $f_j$, respectively. We say that $i<j$, if (1) $f_i<f_j$, or (2) $f_i=f_j$ and $i<j$ in alphabetical order.

We now introduce two major data structures: the Item-Frequency List (IF-list) and the Compressed FP-tree (CFP-tree) in ADMiner. The data structure IF-list consists of a pair of item and its frequency (IF-pair). The IF-pairs form an IF-list and are ordered as stated in Definition 3. The sequence of IF-pairs in an IF-list is unique when a path in the CFP-tree is constructed. The CFP-tree is used to store the items of every transaction in a database. The CFP-tree consists of Compressed FP-Nodes (CFP-node) that store all the items and their subsequence of the same support count.

The formal definition is given below:

Definition 4. Let $S$ be an IF-list in which every element is an IF-pair of the form $\langle i,f_i\rangle$, where item $i\in I$ and frequency $f_i\geq 0$.

Definition 5. A CFP-tree consists of one or more CFP-nodes, and each node is of the form $X$: $f$, where itemset $X\subseteq I$ and $f$ is the frequency of $X$. The root of a CFP-tree is a null itemset with a frequency value of 0.

The examples of IF-list and CFP-tree will be shown later in TABLE and Figure 1 (c), respectively.

The ADMiner algorithm has two phases. The first phase is called the construction phase. In this phase, it constructs the CFP-tree by scanning the database twice. In the first database scan, the ADMiner creates an IF-list to record the information of items and their frequencies. In the second database scan, a CFP-tree is constructed by adding a new path or merging an existing path for every transaction in the database.

The second phase decomposes the CFP-tree as needed for adjustment. The order of item sequence will be changed, as well as the frequency of the items stored in the same node. In this phase, a node may split into two or more new nodes and the order of IF-list is likely to be
changed. Necessary steps are required to make adjustments and obtain a new CFP-tree.

These two phases are described as follows:

Step 1: Scan the original database DB to calculate the frequency of transactions containing the items \(i_j \in I\), where \(j = 1, 2, \ldots, m\).

After processing the last transaction, we have constructed the data structure IF-list which contains all of the items and their frequencies. The elements of IF-list are sorted by frequency in descending order, as described in Definition 3. Next, we start the second scan of DB.

Step 2: Read a transaction from DB and insert each item into the CFP-tree, working down to the end of the original database DB.

Substep 2.1: Read a transaction to get the current sequence of items.

Substep 2.2: Sort the items in the same order of the IF-list.

Substep 2.3: Add the sorted items to the CFP-tree.

To add the sorted Items Sequence of the current transaction (IST) to the CFP-tree, we check the Item Sequence of the Node (ISN) starting from the first leftmost child of the root node. The item sequence of the first transaction, IST(tid 1), will be simply inserted into the first child node of the root. There are five cases in the construction of the rest of the CFP-tree as follows:

Case 1: ISN(node i) = IST(tid j), where i and j are indices for a node and a transaction, respectively.

(1). Increase the support count of node i by 1.

Case 2: IST(node i) ⊂ IST(tid j), where the first item of ISN = the first item of IST.

(1). Increase the support count of node i by 1.

(2). If node i is a leaf node, add a new child node containing the items of IST(tid j) – ISN(node i) and set the support count of the new node to 1.

(3). If node i is not a leaf node, set IST(tid j) = IST(tid j) – ISN(node i) and continue the construction process by checking with the children of node i.

Case 3: IST(tid j) ⊂ ISN(node i), where the first item of ISN = the first item of IST.

(1). Set ISN(node i) = ISN(node i) – IST(tid j) and increase the support count of node i by 1.

(2). If node i is a leaf node, add a new child node containing the items of ISN(node i) – IST(tid j) and set the same support count to the new node.

(3). If node i is not a leaf node, add a new child node containing the items of ISN(node i) – IST(tid j), set the same support count to the new node, and move all the child nodes of node i to become the child nodes of this new node.

Case 4: Node i and IST(tid j) have at least the first c item(s) in common.

(1). Set ISN(node i) = ISN(node i) - all the common items.

(2). Add a new node containing all the common items as the parent node of node i and set the support count to be the support count of node i plus 1.

(3). Set IST(tid j) = IST(tid j) - all the common items.

(4). Add a new node containing the items of IST(tid j) as the child node of node i and set the support count of the new node to 1.

Case 5: Check all the child nodes of the root and do not find a match for the above four cases.

(1). Under the root, add a new child node containing the items of IST(tid j) and set the support count of the new node to 1.

In the second phase, we process the transaction database that has been updated. Since the frequencies of some items have been changed, their corresponding CFP-nodes of the CFP-tree need to be rearranged. To adjust the CFP-tree, we have the following five steps:

Step 1: For an update database DB+ containing new transactions, calculate the frequency of items presented and obtain a new IF-list.

Step 2: Adjust the current tree to match the item order of the new IF-list. Here we move one branch (or path) at a time from the current CFP-tree to a temporary CFP-tree until no branch is found.

Substep 2.1: Remove a branch from the current CFP-tree.

Substep 2.2: Sort it by the item order of new IF-list.

Substep 2.3: Add the sorted item sequence into the temporary CFP-tree.

Substep 2.3.1: Treat the sorted item sequence as a transaction (IST) to be compared with the item sequence of the temporary tree node (ISN).

Substep 2.3.2: Use the same five cases in Step 2 of the first phase to insert the branch into the temporary CFP-tree.

Step 3: Process a transaction at a time in the update database DB+, updating the temporary CFP-tree until the last transaction is done.

Step 4: Move the temporary CFP-tree to become the current CFP-tree.

Step 5: Mine the frequent patterns from the current CFP-tree using the specified min-sup.

IV. EXAMPLES OF THE PROPOSED APPROACH

Examples are presented in three scenarios. First, we show how to construct a CFP-tree for mining frequent itemsets. Second, an incremental mining example for adding a new item sequence to the CFP-tree is provided after a database update. The last example for adjusting CFP-tree after adding a new transaction and deleting the oldest transaction is presented with stream data mining.

<table>
<thead>
<tr>
<th>tid</th>
<th>Items bought</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>A, C, F, M, P</td>
</tr>
<tr>
<td>200</td>
<td>A, B, C, F, M</td>
</tr>
<tr>
<td>300</td>
<td>B, F</td>
</tr>
<tr>
<td>400</td>
<td>B, C</td>
</tr>
<tr>
<td>500</td>
<td>A, C, F, M, P</td>
</tr>
</tbody>
</table>
A. CFP-tree Construction

In the tree construction process, we use the transaction database DB1, as shown in TABLE I. Each row represents a transaction. The first column is the transaction identifier TID and the second column is the items being bought.

<table>
<thead>
<tr>
<th>Item</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>4</td>
</tr>
<tr>
<td>F</td>
<td>4</td>
</tr>
<tr>
<td>A</td>
<td>3</td>
</tr>
<tr>
<td>B</td>
<td>3</td>
</tr>
<tr>
<td>M</td>
<td>3</td>
</tr>
<tr>
<td>P</td>
<td>3</td>
</tr>
</tbody>
</table>

At the beginning, we need to obtain the IF-list by scanning the database and counting the frequency of each item. The items in the IF-list are sorted in descending order, as defined in Definition 3, which guarantees the unique sequence for the CFP-tree to be constructed. In this case, the ordering sequence is C, F, A, B, M, and P, as shown in TABLE II.

![Figure 1. Building a CFP-tree for the original transaction database](image)

After obtaining the IF-list, ADMiner will construct CFT-tree in this step. Before the items of transaction are added to the CFT-tree, their item sequences are sorted in the IF-list. The item sequence of first transaction is C, F, A, M, and P. These items are added to the CFP-tree. According to our rules, items with the same support count will be put into the same node, as shown in Figure 1(a). Secondly, the item sequence of tid 200 becomes C, F, A, B, and M. Since there exists a common path, C, F, and A, the first node will be split into two parts, (C, F, A) and (M, P) such that (M, P) becomes the first child of (C, F, A). After adjusting the tree, the node (B, M) is inserted as the next child node and their support counts are added, as shown in Figure 1(b). The above steps are repeated until all the transactions are processed. The final results are displayed in Figure 1(c).

B. Incremental Data Mining

In the real world, new transactions are added into databases all the time. To mine the database incrementally, ADMiner processes the new transactions efficiently without rescanning the original database. For simplicity, we use the first three transactions in TABLE I as the original increment database (DB2), and the remaining two transactions are regarded as the addition transaction database (DB3).

<table>
<thead>
<tr>
<th>Item</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>3</td>
</tr>
<tr>
<td>A</td>
<td>2</td>
</tr>
<tr>
<td>B</td>
<td>2</td>
</tr>
<tr>
<td>C</td>
<td>2</td>
</tr>
<tr>
<td>M</td>
<td>2</td>
</tr>
<tr>
<td>P</td>
<td>1</td>
</tr>
</tbody>
</table>

First, we use DB2 to build a CFP-tree. Then we apply the transactions in the addition database DB3 to update DB2 and its CFP-tree. The incremental mining process is summarized in the following steps.

**Step 1. Adjust the CFP-tree**

Before performing the database update, a CFP-tree is constructed in the CFP-tree1 of Figure 2(a) and the order of item sequencing is F, A, B, C, M, and P, as shown in TABLE III. We then scan the addition database DB3 to update the IF-list and the results are shown in TABLE IV. The order of item sequencing has been changed to C, F, A, B, M, and P. Therefore, our CFP-tree must be adjusted.

![Figure 2. Incremental Data Mining](image)

**Step 2. Update the CFP-tree using the addition transactions**

In Figure 2 the original CFP-tree is constructed under CFP-tree1, and CFP-tree2 is used to hold the new CFP-tree after the adjustment.

First, we remove the path (F, A, C, M, P) from Figure 2(a), resort it to become (C, F, A, M, P), as based on the order in TABLE III, and add the results to CFP-Tree2 as shown in Figure 2(b). Similarly, we remove the path (F, A, B, M), resort it to become (C, F, A, B, M), and add it to CFP-Tree2. The above steps are repeated until no path is left in CFP-Tree1. The results of CFP-Tree2 are shown in Figure 2(c). Then, transactions tid 400 and tid 500 are added into CFP-Tree2, as shown in Figure 2(d).
C. Stream Data Mining

Since the deletion transaction simply causes a reverse effect on the database and the CFP-tree, ADMiner can take care of deletion as long as the deleted items (and itemsets) exist in the previous transactions.

To demonstrate this capability, we use stream data mining as an extension of ADMiner. To mine stream data in a fixed size window, newly arriving transactions are added into the window while the old ones are removed. This works with the above assumption that our approach can delete existing items and itemsets. The rest of this section will give a simple example which shows how to perform stream data mining using ADMiner.

### Table V.

<table>
<thead>
<tr>
<th>IF-List of tid 200 and tid 300</th>
</tr>
</thead>
<tbody>
<tr>
<td>B F A C M P</td>
</tr>
<tr>
<td>2 2 1 1 1 0</td>
</tr>
</tbody>
</table>

As before, we use the transaction database DB2. In this example, the window size is 2. That means we only keep two transactions in our CFP-tree at a time.

![Figure 2. CFP-tree construction and incremental update](image)

(a). The original CFP-tree is constructed under CFP-Tree1

(b). Remove the path (F, A, C, M, P) from CFP-Tree1 of Figure (a) and add it to CFP-Tree2

(c). Remove the path (F, A, C, B, M) and (F, B) from CFP-Tree1 of Figure (b) and add it to CFP-Tree2

(d). Insert tids 400 and 500 (DB3) into CFP-Tree2

![Figure 3. CFP-tree construction for window-based stream data mining](image)

(a). Insert tid 100 and tid 200 into CFP-Tree1

(b). Delete tid 100 (A, C, F, M, P) from CFP-Tree1 of Figure (a)

(c). Remove the path (A, C, F, M, B) from CFP-Tree1 of Figure (b) and add it to CFP-Tree2

(d). Insert tid 300 into CFP-Tree2

Figure 3. CFP-tree construction for window-based stream data mining

To begin, we construct the CFP-tree using the same construction process. The first window has the first two transactions of DB2, tid 100 and tid 200. They are added into the FP-Tree1, as shown in Figure 3 (a).

Next, tid 200 and tid 300 are in the second window. Hence, we delete transaction tid 100 and insert
transaction tid 300. The IF-list is updated, as shown in TABLE. We get the item sequence B, F, A, C, and M.

The next step is to adjust the tree. Since transaction tid 100 (A, C, F, M, P) is deleted, we remove its items from the tree, as shown in Figure 3 (b). Then, as described in the Incremental Data Mining section, we use the assemble-and-detach approach to adjust the tree based on the IF-list. The path A, C, F, M, and B is removed from CFP-Tree1 and inserted into CFP-Tree2 in a new order of B, F, A, C, and M, as shown in Figure 3 (c). Then transaction tid 300 (B, F) is inserted into the new CFP-Tree2, as shown in Figure 3 (d). The final step is to replace CFP-Tree1 with CFP-Tree2 in preparation for the next run of database updating.

V. EXPERIMENTS

A. Experimental Environment

We implemented ADMiner in Java with JDK 1.6. The experiments are all performed on a 2.66GHz Intel Core 2 Duo CPU with 4GB DDR2 memory and running Microsoft Windows XP SP2.

Some of the datasets used for the experiments are produced by the IBM dataset generator [15]. The length of each itemset follows a Poisson distribution whose mean is equal to L. The parameters for generating these datasets are shown in TABLE.

<table>
<thead>
<tr>
<th>Parameters Used for IBM Dataset Generator</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
</tr>
<tr>
<td>T</td>
</tr>
<tr>
<td>I</td>
</tr>
<tr>
<td>L</td>
</tr>
<tr>
<td>N</td>
</tr>
</tbody>
</table>

In order to fairly evaluate ADMiner, a real dataset called BMS-POS [16] and several other datasets are used in our experiments. The BMS-POS dataset records several years of sales data from electronics retailers. Each transaction of the dataset represents the items a customer bought at one time. There are 515,597 transactions and 1,657 items in the dataset.

<table>
<thead>
<tr>
<th>The Number of Nodes with BMS-POS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset</td>
</tr>
<tr>
<td>--------</td>
</tr>
<tr>
<td>BMS-POS</td>
</tr>
</tbody>
</table>

B. Experimental Results

We use the BMS-POS dataset to perform experiments on the traditional FP-tree algorithm and ADMiner. The results are shown in Figure 4. It can be observed that the total node numbers of the traditional FP-tree are four times greater than ours. This shows that the traditional FP-tree uses more memory space than ADMiner. Thus, our approach can process more transactions and items with limited memory.

In order to show the scalability of ADMiner in terms of the CFP-tree size, we divided the BMS-POS dataset into five partitions. Each partition has 100k transactions. The experimental results of memory usage are shown in Figure 4. It is obvious that the traditional FP-growth algorithm has a rapid increase in number of nodes when the number of transactions ranges from 100K to 500K. ADMiner has better scalability performance and uses less memory than the traditional FP-growth algorithm.

In Figure 5, we can see that the execution performance of ADMiner is better than that of the traditional FP-growth algorithm. Because the tree size of ADMiner is smaller than the traditional FP-tree, traversing the whole tree requires less time.

We also use the T10I4D100K dataset to measure ADMiner. The T10I4D100K dataset was generated by the IBM generator. This dataset has a total of 100,000 transactions and 999 distinct items. The results are...
shown in TABLE. In this experiment, it can be observed that the total number of the traditional FP-tree nodes is 714730 and the number of our CFP-tree nodes is 113511. The number of nodes in the traditional FP-tree is six times that of our CFP-tree.

We also divided the T10I4D100K dataset into five partitions to show the scalability of ADMiner. Each partition has 20k transactions. The experimental results of memory usage are shown in Figure 6. We can see that the traditional FP-growth algorithm has a rapid increase in node number as the number of transactions increases from 20k to 100k. The comparison of execution times is shown in Figure 7, where the performance of ADMiner is better than that of the traditional algorithm. When the minimum support is greater than 2.5%, the number of frequent itemsets decreases and the advantages of ADMiner also go down.

TABLE VIII.
THE NUMBER OF NODES WITH T10I4D100K

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Traditional FP-tree nodes</th>
<th>CFP-Tree nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>T10I4D100K</td>
<td>714730</td>
<td>113511</td>
</tr>
</tbody>
</table>

For dense datasets, we use a real world chess dataset [16] for our experiments. This dataset has a total of 3190 transactions and 75 distinct items. The results are shown in TABLE. The number of nodes in the traditional FP-tree is six times that of our CFP-tree.

TABLE IX.
THE NUMBER OF NODES WITH CHESS DATASET

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Traditional FP-tree nodes</th>
<th>CFP-tree nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>chess</td>
<td>38609</td>
<td>5800</td>
</tr>
</tbody>
</table>

Figure 6. The comparison of the number of nodes with T10I4D100K dataset.

We also divided the chess dataset into five partitions to show the incremental update application (addition) of ADMiner vs. that of the traditional FP-tree algorithm. Each partition has 0.6k transactions. Experimental results of memory usage are shown in Figure 8. From these results, we can see that the traditional FP-tree algorithm has a rapid increase in node number when the number of transactions ranges from 0.6k to 3k. The comparison of execution times is shown in Figure 9. We can see the performance of ADMiner is better than that of the
traditional algorithm when the minimum threshold is less than 80%.

From the above experiments, we know that ADMiner uses less memory than the traditional FP-tree. On average, the node number in the traditional FP-tree is five times that of our CFP-tree. The same is true for the execution time since our CFP-tree is much smaller than the traditional FP-tree.

C. Discussion

First, we discuss some situations which may influence the performance of ADMiner. If the transaction database DB is a dense dataset, there will be many common paths. This means that many common branches can be shared in a tree. Thus, our CFP-tree is much smaller than a traditional FP-tree and has many advantages. ADMiner can process a larger number of transactions and items with limited memory, and also traverse the tree quickly.

On the other hand, if the transaction database is a sparse dataset, our CFP-tree is still smaller than a traditional FP-tree. Although our tree will be wider than that of a dense dataset, it can still save memory space. However, because there are less common paths, it needs to search more nodes than a dense dataset does. Hence, it takes more time during node searching, but the memory usage is still very efficient.

VI. CONCLUSIONS AND FUTURE WORK

In real world applications, data mining algorithms often face the problems of huge databases and routine updates. Since memory space is limited, processing the updated database without rescanning the original one is a critical issue. We propose an improved data structure based on FP-tree to process more transactions using limited memory. In addition to saving memory, ADMiner deals with the incremental mining of the dynamic database by using the results of previous mining processes.

In future research, we will make further improvements and adjustments to the CFP-tree and apply our approach when mining closed itemsets [17], sequential patterns [18] and global-local frequent patterns [19].

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REFERENCES

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