An Algorithm towards Indexing Evolving Graph Databases

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Abstract— In the field of extracting valuable information or knowledge from large database, data mining is a powerful tool. Frequent substructure mining, also denoted by graph mining, requires searching for frequent substructures or sub-graphs from large structured or graph database. \textit{gIndex} is a more robust algorithm for mining graphs, especially for indexing frequent sub-graph patterns over previous Apriori or path based graph mining algorithms. \textit{gIndex} finds the super-graphs of the given query graph from the graph database. The main specialty of \textit{gIndex} is to maintain an index of graph database according to discriminative fragments. This research work proposes a further improvement over the existing \textit{gIndex} algorithm. The proposed algorithm in this paper is specially designed for handling sudden change in database graph patterns. The algorithm, \textit{EGDIM}, is capable of processing queries in dynamic and evolving database which \textit{gIndex} can not handle. To achieve the same performance for evolving graph databases, more information is stored in the index data structure to quickly answer the graph query, discarding the unnecessary graphs. \textit{EGDIM} also ensures a good running time for processing graph queries in the evolving graph databases.

Index Terms— Data mining, Knowledge discovery, Graph mining, Indexing.

I. INTRODUCTION

The process of discovering knowledge and determining patterns and their relationships by analyzing large database is called data mining. Frequent patterns are patterns (such as itemsets, subsequences, or substructures) that appear in a data set frequently [10, 11]. \textit{Apriori} algorithm is an innovative way to find association rules on large scale databases, allowing implication outcomes that consist of more than one item. Despite the simplicity of Apriori algorithm, it is costly for mining frequent itemsets in large database, so \textit{FP-growth} [10] approach is proposed for better performance.

Structured data mining is the process of finding and extracting useful information from semi-structured data sets. Frequent substructure mining is a special kind of frequent pattern mining [1, 2]. Graphs are widely used data structures for representing schema less data in biological, chemical and other important fields. A new and special field of data mining, \textit{Graph Mining}, is used to mine data, or sub-graphs, from complicated structures. Graph represents not only the properties of the elements, but also the relationship between the elements. The main challenge to solve the problem of processing sub-graph queries on a database, by finding the set of graphs in the database that are super-graphs of the query, is the size of the database and the NP completeness of sub-graph isomorphism problem [3, 4, 5, 6].

In Graph mining, we have to be able to search in the database for the presence of a query graph. In the core of graph mining problem, there lies the \textit{sub-graph query problem}. \textit{Apriori}-based frequent substructure mining algorithms, which proceed in a bottom-up manner and adopt a level-wise mining methodology, share similar characteristics with Apriori-based frequent itemset mining algorithms. The problem of Apriori based algorithm is, it generates duplicate patterns and scans the database many times. In order to avoid such overhead, non-Apriori-based algorithms have recently been developed, most of which adopt the pattern-growth methodology like \textit{gSpan} [1] and \textit{GraphGrep} [9]. \textit{gSpan} algorithm and \textit{GraphGrep}, which are path based graph mining algorithms, were not efficient to search the whole database for answering the graph query. For answering graph queries faster, an index of the graph database can be [7, 8] kept. Both frequent pattern and path or substructure can be used as indexing feature. For faster query search, an improved version of graph mining algorithm, \textit{gIndex} [2] is proposed, which uses frequent substructure as its indexing feature. \textit{gIndex} builds graph indices to help processing graph queries and retrieve related graphs and is used in indexing sequences, trees, and other complex structures.

Features of \textit{gIndex} algorithms are, \textit{size-increasing support constraint}, that uses low minimum support on small fragments for effectiveness and high minimum support on large
fragments for compactness, discriminative fragments as indexing feature and Apriori pruning, that enables glindex to optimize its efficiency.

Although paths are easy to manipulate and taking paths as the indexing feature leaves the indexing space predefined, frequent substructures, being more expressive in representing the properties of a graph, preserving the structural information, are ideal candidate for the indexing feature. The problem of glindex is, it only takes into account those frequent substructures which are discriminative enough and assumes that the database is stable to updates. Performance of glindex degrades due to random growth of database, because it does not take into account any nearly frequent substructures.

This research extends the existing glindex algorithm to achieve an even better performance for evolving database. A new method, EGDIM (Evolving Graph Database Indexing Method), is proposed, which keeps track of the recent semi-frequent substructures having support close to minimum support. These semi-frequent substructures are considered as indexing features when their support reaches the minimum support. An idea to remove the least recently encountered discriminative frequent sub-structure from the index structure is also proposed for memory efficiency.

II. PRELIMINARIES

Some terms and definitions required for the understanding of EGDIM algorithm is discussed in this section.

Definition 1. Graph isomorphism: In graph theory, an isomorphism of graphs A and B is a bijection between the vertex sets of A and B, f : V(A) → V(B), such that any two vertices u and v of A are adjacent in A if and only if f(u) and f(v) are adjacent in B [12].

Definition 2. Sub-graph isomorphism problem: The sub-graph isomorphism problem is a computational task in which, given two graphs A and B, one must determine whether A contains a sub-graph that is isomorphic to B [13].

Definition 3. Support or Frequency: Given a labeled graph data set, D = {G1, G2, ..., Gm}, we define support(g) or frequency(g) as the percentage (or number) of graphs in D where g is a sub-graph [10]. |Dg| is the number of graphs in D where g is a sub-graph [2].

Definition 4. Minimum support: For a database D, and a timestamp T, a value is defined as the minimum threshold for support to identify fragments for further consideration. It is called minimum support or min_sup in short.

Definition 5. Frequent fragment: A frequent fragment (or graph, sub-structure, sub-graph) is a graph whose support is no less than min_sup [10].

Definition 6. DFS code and DFS lexicographic order: DFS code is an edge sequence for subscribing graphs to build an order among different graph sub-scripting.

Definition 7. Minimum DFS code: Based on the DFS lexicographic ordering, the minimum DFS code of a given graph G, written as dfs(G), is the minimal one among all the DFS codes. The subscripting that generates the minimum DFS code is called the base subscripting.

Definition 8. Feature set: The set of sub-graphs that are considered as a property of a graph. The graph feature set is denoted by F. For any graph feature f ∈ F, Df is the set of graphs containing f. Df = {g | f ⊆ g, g ∈ Df} [2].

Definition 9. Candidate query answer set: The first step of query processing, searching, enumerates all the features in a query graph, q, to compute the candidate query answer set, Cq = ∩f∈F Df (f ⊆ q and f ⊆ F). Each graph in Cq contains all q’s features in the feature set. Therefore, Dq is a subset of Cq [2].

Definition 10. Redundant fragment: Fragment x is redundant with respect to feature set F if Dx ≅ ∩f∈F Df or Df [2]. That means if a fragment's presence can be predicted by the presence of it’s sub-graphs, then it is a redundant fragment.

Definition 11. Discriminative fragment: Fragment x is discriminative with respect to feature set F if Dx ≅ ∩f∈F Df or Df [2].

Definition 12. Prefix tree: It is an efficient tree data structure used for indexing graphs according to their prefixes after translating fragments into sequences.

III. EGDIM EVOLVING GRAPH DATABASE INDEXING METHOD

Although glindex started a new way to answer the sub-graph queries through an indexing approach, it has some drawbacks. The main drawback of glindex algorithm is that, when it starts with small size of initial database, it creates a lot of fragments which are not necessary for indexing and it also may discard fragments which may be frequent on later updates. Another lacking of glindex is, it can not handle random change in database updates. This lacking occurs because glindex only stores the fragments which have their frequencies above the minimum support. For the absence of this feature, once the preprocessing is done in glindex algorithm, if fragments, having frequencies close to the minimum support, are encountered later, they will not be added to the glindex tree, no matter how many times they are encountered.

To overcome the drawbacks of glindex algorithm, we propose a modified approach, EGDIM, over glindex algorithm. Here, at the beginning of frequent fragment selection process, not only the fragments which have frequencies above the minimum support is stored, but also track of fragments having frequencies close to the minimum support is kept. Although EGDIM can handle dynamic or evolving data in the updates of the database, the main drawback of this approach was, it needs extra memory space for storing new fragments, where reducing memory space is one of the major properties of glindex. To overcome this problem, in EGDIM, if a fragment is very old (according to its use or update), then that fragment is removed. That means EGDIM removes the LRU (least recently used) fragment from stored database for semi-frequent fragments.

Five phases of EGDIM are similar to glindex algorithm but adds some improvements for performing well in dynamic database. The first two phases are for building the initial index.
tree from the given database. The next three phases are for incremental updates. We will describe the phases with appropriate example in this section for the sample graph database shown in figure 1.

\[
\begin{array}{c}
S \rightarrow C \rightarrow C \rightarrow N \rightarrow C \rightarrow S \rightarrow C \\
O \rightarrow O \rightarrow O \rightarrow O
\end{array}
\]

Figure 1: Example graph database

In discriminative fragment selection phase, all frequent fragments according to size-increasing support constraint are generated. To generate these fragments, simple BFS (breadth first search) approach is used. BFS approach is used for the level-wise expansion of the fragments, which helps to differentiate the discriminative fragments from the redundant fragments. We take into consideration the discriminative fragments, and eliminate the redundant fragments. As some fragments of the graph database (redundant fragments) are not considered for later computation, it saves a lot of space as well as minimizes the query processing time. Algorithm 1 provides the pseudo code for the discriminative fragment selection phase.

**Algorithm 1. Feature selection algorithm**

**Input:**
Graph database, \( D \),
Discriminative ratio, \( \tau_{disc} \),
Size-increasing support function, \( \rho(l) \),
Maximum fragment size, \( max_l \),
Constant needed to store the temporary fragments, \( k \),
Minimum support, \( min_{sup} \).

**Output:**
Feature set, \( F \),
Temporary feature set, \( T \).

**Method:**
1. let \( F = \{f\} \), \( T = \{f\} \), \( D_{\{f\}} = D \), and \( l = \emptyset \)
2. while \( l \leq max_l \), do
3. for each fragment \( x \), discriminative and having size \( l \) do
4. if \( x \) is frequent then
5. \( F = F \cup \{x\} \)
6. else if \( x \) \( \in \) set of previous \( k \times min_{sup} \) graphs
7. \( T = T \cup \{x\} \)
8. \( l = l + 1 \)
9. return \( F, T \)

In the process of keeping semi-frequent fragments, only fragments from last \( constant \times min_{sup} \) graphs are stored, regardless of their being frequent or not. If the minimum support for a database is \( min_{sup} \), then all fragments available from the last \( k \times min_{sup} \) graphs of the database are kept. Here, \( k \) is an integer constant, set to a value prior to the algorithm execution according to the assumed randomness of graphs in the database. Setting the correct value of \( k \) is a vital point of improvement for EGDIM algorithm. It is because the more the value of \( k \) is, the more EGDIM algorithm can cope up with random occurrences of graphs in database.

In index construction, canonical labeling is used. For canonical labeling, DFS code is introduced. If two graphs are isomorphic, they will share the same minimum DFS code. By using the minimum DFS code, each fragment can be mapped into an edge sequence of discriminative fragments in a prefix tree. This tree is also referred as \( gl\) index tree. The prefix tree records all \( n \)-sized discriminative fragments in level \( n \). Figure 2 shows an example prefix tree.

In the index tree, code \( s \) is an ancestor of \( s' \) if and only if \( s \) is a prefix of \( s' \). In the prefix tree, all discriminative nodes and some redundant nodes are present. All leaves of the tree are discriminative nodes and each has an \( id \) list.

In the search section, for a query graph, \( q \), like \( gl\) index, EGDIM algorithm also enumerates its fragments up to a maximum size and searches matches for them in the index tree. Then it generates a set by intersecting the sets of \( id \) lists associated with these fragments and generates the candidate

Figure 2: Prefix tree

Figure 3: Nodes are linked according to the access time
set, \( C_r \), with the respective graphs of the id list. **Apriori pruning** and **hashing** is used in this section.

To check whether graphs in the candidate set are actually super-graphs of the query graph, the candidate graphs are checked one by one and sub-graph isomorphism test is run.

**Verification** approach in **EGDIM** algorithm is almost same as the verification approach used in **gindex** algorithm except, whenever a discriminative fragment is found, the current time in that node is stored as its last access time and link list is updated. To maintain track of time, a **global time counter** is kept, which is incremented after any kind of instruction execution. For example, if we find a discriminative node which has a current access time of 10, as shown in **figure 4**, and value of the global time counter is 22, the value of last access time of that node will be updated. For each time a node’s access time counter is updated, it will surely hold the largest value so far, so, it is very easy to update the link list in \( O(1) \) time complexity. The updated link list for the example is shown in **figure 5**.

In the **maintenance** section for insertion, the fragments available from the last \( k \times min \_sup \) graphs in the database are kept in a temporary section. When inserting a new fragment, it is checked if this fragment became frequent with respect to the temporary stored data, illustrated in **Figure 6**. If the new fragment becomes frequent, then we add it to the prefix tree. The maintenance algorithm is shown in **algorithm 2**.

**Algorithm 2. Maintenance algorithm**

**Input:**
- Feature set, \( F \)
- Temporary feature set, \( T \)
- Link list head, \( Head \)
- Link list tail, \( Tail \)
- Threshold time, \( Q \)

**Method:**
1. for each fragment \( x \)
2. if \( x \in F \) then
3. update \( x . graph \_id \_list \)
4. else
5. \( T = T \cup \{ x \} \)
6. if \( |x . graph \_id \_list| \geq min \_sup \) then
7. \( F = F \cup \{ x \} \)
8. \( T = T - x \)
9. while \( curr \_time - Head . last \_access \_time > Q \)
10. \( Head = Head . next \)

**Figure 6:** (i) Temporary fragment set (ii) Current data (iii) New frequent fragment

Another improvement, proposed in the maintenance section, is to check the link list for storing the last access time of fragments. If the oldest node is not accessed for a **defined threshold time**, then it is removed from the link list as well as from the prefix tree. The algorithm keeps checking the link list as long as a node is found in the link list which has been accessed within the threshold time period.
IV. EXPERIMENTAL RESULTS

In this section, performance evaluation of EGDIM is focused using several scenarios to compare EGDIM algorithm with glIndex algorithm for mining frequent graphs from an evolving graph database and cases where the algorithms start with a small size of initial database are also discussed.

We worked on chemical data set collected from [14]. The data set was fed to the algorithms sequentially to make them behave as evolving data set. The experiment on various values for the minimum support was performed and tested using several queries. Given a query, the performance was measured with the number of super-graphs answered by the algorithms.

Figure 9 shows an experimental result. Here, the initial database size was different for different test sets. As the size of initial database increases, both the glIndex and EGDIM algorithm converges to the actual result. But, initially, for very small size of initial database, EGDIM algorithm outperforms glIndex algorithm. For later cases, EGDIM algorithm performs at least as much as glIndex algorithm but no less than it. The value of $k$, a constant needed to store the temporary fragments in EGDIM algorithm, was set to 3 and minimum support was set to 2. Two new graphs were inserted to the initial database and it is showed that glIndex does not perform well enough where EGDIM algorithm copes up with the change of the database.

Figure 11: Comparison between glIndex and EGDIM algorithm for various numbers of new inserted graphs into the initial database for different sets of queries

Figure 12: Performance of EGDIM algorithm for various values of $k$ for a fixed number of queries
For various values of $k$, the constant to decide how many fragments will be stored from the new updates, EGDIM algorithm responses in different ways shown in Figure 12. As the value of $k$ increases, more fragments will be stored in the temporary memory and probability of answering the query properly will increase. As this performance comes with the cost of memory, it is necessary to select a suitable value of $k$ that will enable EGDIM to perform optimally.

Another important issue is, if more fragments of each graph are stored, it also increases the probability of proper response to the query. Figure 13 shows an experimental result on various numbers of fragments stored for each graph in the database. When the amount of fragments stored is increased, EGDIM algorithm's response tends to 100% accuracy. As it is memory consuming to store too much fragments, we have to face a trade-off in selecting the value of $k$. Tuning the proper value for $k$ and number of fragments to be stored in the memory for each graph, is a vital and sensitive issue.

The main part we have focused in EGDIM algorithm is the candidate set generation phase. EGDIM algorithm focuses on providing correct result with the cost of memory space. Experimental result also proves this fact that EGDIM algorithm performs better with evolving data than glindex algorithm. It will never give a wrong result when glindex will provide a right one.

V. CONCLUSION

In this research work, an idea to improve the existing glindex algorithm is developed to make it work for evolving database. EGDIM algorithm, using some extra memory space, stores some fragments of new updates of database and easily adjusts with evolving databases, where glindex algorithm was unable to work properly with small sized initial database and cope up with dynamic change in database updates. Maintaining a link list for keeping track of the access time of the fragments is necessary in EGDIM, because it identifies the least recently accessed fragment in the index tree. Deletion of unnecessary fragments, which helps in providing extra memory space necessary for storing extra fragments, were also presented in EGDIM. As the experiments reflect, EGDIM algorithm performs better in the field of evolving databases than glindex algorithm. This result is showed with the help of small sized initial database and later sequential updates of the database. Although EGDIM algorithm's performance may be slower than glindex in a few cases, it will guarantee more accurate result than glindex.

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