



Evaluation of Proposed Algorithm with Preceding GMT for Fraudulence Diagnosis

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ABSTRACT

Formerly existing graph mining algorithms regularly accept that database is generally static. To defeat that we proposed another algorithm which manages extensive database including the components which catches the properties of the graph in a couple of parameters and check the relationship among them in both left and additionally right course, in this way embracing DFS and in addition BFS approach. It furthermore discovers the subgraph by traversing the graph and removing the planned routine. The proposed calculation is utilized for identification of wrongdoing as a part of BANK & Financial organization by catching the properties and distinguishing the relationship and affiliations that may exist between the individual required in that wrongdoing which keep a few violations that may happen in future. We have utilized the Neo-ECLIPSE for the execution of proposed calculation and Neo4j is the graph database utilized for evaluation. On the off chance that a man endeavoring to confer fraud or engage in some kind of illicit movement, they will endeavor to pass on their activities as near authentic activities as could reasonably be expected. Here in this paper, we are giving the data that a man who is in beginning the phase of the fraud, what co-related wrongdoings or illicit exercises he can do in future. The future exercises that can be performed by the individual can be ceased by demonstrating the associations with the entries saved in the database.

Keywords: Part Miner, gSPAN, gIndex, Graph database, Traversing.

INTRODUCTION

These days the measure of information is expanding step by step, so appropriately the longing for information mining is likewise developing. The substantial database must be looked to locate the fascinating properties of the graph and to build up a relationship along with them. It is gainful to

demonstrate the complex data with the assistance of graph in which data is stored in nodes and edges speak to the relationship among the nodes^{1,2}. Subsequently having a Graph database defeats the important of a relational database and helps in finding the supergraph, subgraph, basic graph and connection in between different graphs. This graph based information mining has turned out

to be increasingly well-known in the most recent couple of years³. Graph mining is the utilization of most essential structure of graph to acquire regular patterns of data. It has board scope of uses⁴.

This graph-based data mining has turned out to be increasingly famous in the most recent couple of years. Graph mining is the utilization of most essential structure of graph to get regular patterns of data. It has board scope of applications. This procedure can be utilized to discover the possibility of persons doing wrongdoing in the organization through the web or by using any other way. Some relevant researchers of individuals required in digital wrongdoing were concentrated on to get the characteristics, for earning, persons required in wrongdoing, whether they are taught or not, style of wrongdoing, acquiring from the specific risk⁵. These feature lead to the development of graph database and algorithm happens to be proposed for traversing the graph in both headings left and in addition right and build up relationship among various nodes which assist creates a sub graph as per the request.

Neo4j is the graph database utilized for evaluation as the recovery times of graph database are not exactly social database as it takes a look at records, it doesn't check the whole gathering to discover the nodes that met the inquiry criteria^{14,7}. Analysis report from this execution will likewise be useful in arranging the prevention concerning a number of offenses. The rest of this paper is sorted out as takes after.

Part 2: presents the issue proclamation of graph based information mining and existing calculations;

Part 3: illustrates our proposed calculation utilized for traversing the graph database;

Part 4: present similar investigation of our proposed system with other existing procedure;

Part 5: conclude Conclusion and future expansion.

Overview of Existing Algorithm

Part Miner Algorithm

Every graph in the database is divided into littler subgraphs. Part Miner can viably diminish the quantity of candidate graphs by examining the total

data of the units. This has prompted a considerable measure of cost investment funds saving. Part Miner is successful and adaptable in discovering subgraphs⁶.

Algorithm Graph Part

Input: G, the graph

Output: G1, G2, the two subgraphs of G

1: $V = \{\text{vertices sorted according to}$

Their update frequency};

2: $V^* = \Phi$;

3: $w(V^*) = \text{""}$

4: for ($i = 0$; $i < |V|/2$; $i++$) {

5: $V_i = \Phi$;

6: call DFSScan(V, i, V_i);

7: Compute $w(V_i)$;

8: if ($w(V_i) > w(V^*)$) {

9: $w(V^*) = w(V_i)$;

10: $V^* = V_i$;

11: }

12: }

13: $G1 = \{e_{ij} = (v_i, v_j) | v_i \in V^*, v_j \in V^*\}$

$\cup \{e_{ij} = (v_i, v_j) | v_i \in V^*, v_j \notin V^*\}$

14: $G2 = \{e_{ij} = (v_i, v_j) | v_i \notin V^*, v_j \in V^*\}$

$\cup \{e_{ij} = (v_i, v_j) | v_i \notin V^*, v_j \notin V^*\}$

Procedure DFSScan(V, i, V_i)

15: stack = $\Phi, m = 0$;

16: stack.push(v_i);

17: while(stack $\neq \Phi \wedge m \leq |V|/2$) {

18: $v = \text{stack.pop}()$;

19: $V_i = V_i \cup \{v\}$;

20: $m++$;

21: choose the neighbor vertex vh ,

s.t. $vh.visited = 0$, and $v \in E, vs.visited = 0 \wedge (v, vs) \in E, vs.ufreq < vh.ufreq$;

22: stack.push(vh);

23: }

Dividing graph database into units

Procedure DBPartition(D, k)

D , graph database;

K : number of units

1: $D_0, 0 = D$;

2: $i = 1$;

3: $l = \log_2 k$;

4: while ($i \leq l$) {

5: for ($j = 0$; $j < 2^{i-1}$; $j++$)

6: DivideDBPart($D_{i-1,j}, D_{i-2,j}, D_{i-2,j+1}$);

```

7: i++;
8: }
9: for (j = 0; j < k - 2l; j++)
10: DivideDBPart(Di-1,j , U2j , U2j+1);
    
```

Function DivideDBPart(Ds, D1,0, D1,1)

```

1: D1, 1 = Φ;
2: D1, 1 = Φ;
3: for each graph G ∈ Ds {
4: G1, G2 = calling GraphPart(G);
5: D1, 0 = D1, 0 U {G1};
6: D1, 1 = D1, 1 U {G2}
    
```

gSpan Algorithm

Graph-Based Substructure Pattern Mining that introduced the gSpan algorithm which usually finds out regular substructures without having candidate production. gSpan develops a new lexicographic arrangement among the graphs and routes every graph to an exclusive minimum DFS code as the canonical label. Dependent upon this lexicographic order, gSpan explores the depth-rst search approach to exploit regularly connected subgraphs effectively^{7,8}. So, gSpan outperforms FSG by the order of degree as well as is suitable to exploit huge regular subgraphs in a larger graph arranged with lower minimal help.

GraphSetProjection(D,S)

1. arrange the labels in D by their regularity;
2. eliminate occasional vertices and edges;

```

3: relabel the leftover vertices and edges;
4: S1 – all regular 1-edge graphs in D ;
5: sort S1 in DFS lexicographic order;
6: S – S1
7: for every edge e ∈ S1 do
8: initialize s alongside e, set S. D
   by graph which includes e
9: SubgraphMining( D,S,s);
10: .D – D-e
11: if |D| < min Sup
12: break;
    
```

Subprocedure 1 SubgraphMining(D,S,s)

```

1: if s ≠ min(S)
3: S – S U
4: specify s in every graph in D
   and count its children;
5: for each c, c is s' child do
6: if support (C) > min Sup
7: s – c
8: SubgraphMining(D,S,s_);
    
```

gIndex Algorithm

Assorted out from the established route-based techniques, this strategy, known as gIndex, will make use of regular substructure as the fundamental categorization or indexing property⁹. Frequent substructures tend to be appropriate candidates considering that they search the internal attributes of the information as well as is reasonably steady to database upgrades¹⁰.

Table1: Comparison of existing algorithm with proposed algorithm

| Feature | Part Miner | gSpan | gIndex | R-MAT | Proposed Algorithm |
|--|--------------|--------------|---------------------------|----------------|-------------------------------|
| Sorting Approach | Yes | Yes | No | No | Yes |
| Search | Up-down DFSS | Up-down DFSS | Up-down DFSS | Up-down DFSS | Both ways Left to right, DFSS |
| Partition Big DB Graph Property Relation | Yes Avg. No | No Good No | Yes Avg. Feature based No | Yes Avg. No No | No Good Yes Yes |

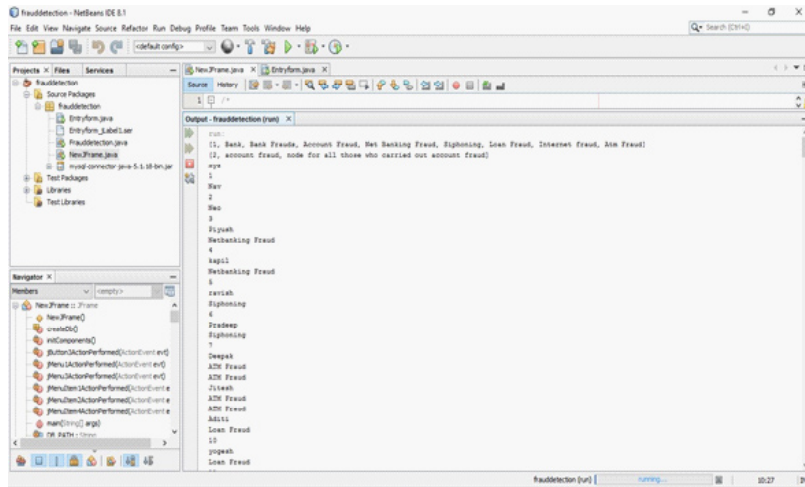


Fig. 1: Overview when database created

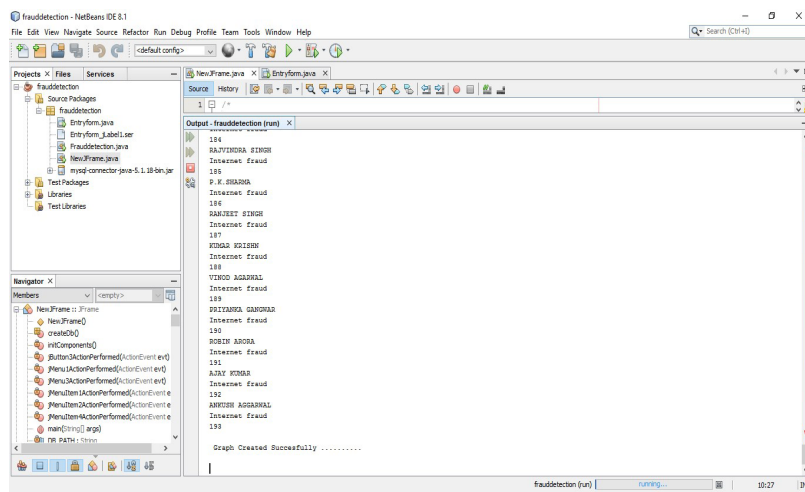


Fig. 2: Overview when database created

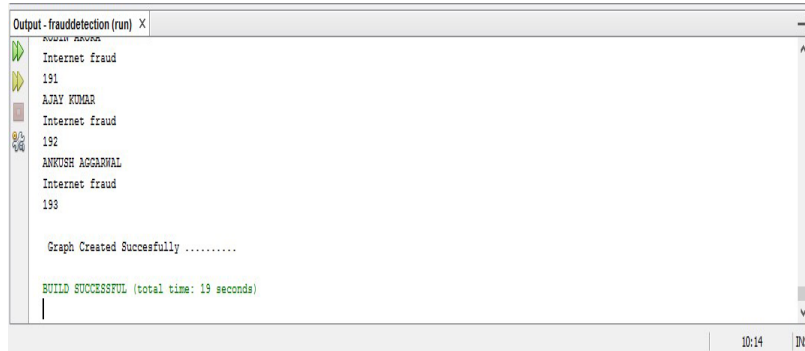


Fig. 3: Overview when database created

Algorithm 1 Feature Selection

Input: Graph database D, Discriminative ratio, Size-increasing support function, Maximum fragment size max L.

Output: Feature set F.

- 1: let $F = \{ f \in \Phi \}$, $Df \in D$, and $l = 0$;
- 2: while $l \leq \max L$ do
- 3: for each fragment x, whose size is l do
- 4: if x is frequent and discriminative then
- 5: $F = F \cup \{x\}$
- 6: $l = l + 1$;
- 7: return F;

Algorithm 2 Search

Input: Graph database D, Feature set F, Query q, Maximum fragment size max L.

Output: Candidate answer set Cq.

- 1: let $Cq = D$;
- 2: for each fragment x is subset of q and $len(x) \leq \max L$ do
- 3: if $x \in F$ then
- 4: $Cq = Cq \setminus Dx$ and return Cq.

Algorithm 3 Insert/Delete

Input: Graph database D, Feature set F, Inserted (Deleted) graph g and its id gid, Maximum fragment size maxL.

- 1: for each fragment x is subset of g and $len(x) \leq \max L$ do
- 2: if $x \in F$ then

- 3: Insert Insert gid into the id list of x;
- 4: Delete; delete gid from the id list of x;
- 5: Return;

RMAT Algorithm

Inside this specific recursive system for the graph, mining discovering the attributes of genuine graphs which appear to continue more than several procedures¹¹. We identify such “laws” as well as, more significantly, suggest a straightforward, parsimonious method, the recursive matrix (R-MAT) system, which could rapidly produce accurate graphs, recording the importance of every single graph in a mere a couple of variables. R-MAT immediately creates graphs using the neighborhoods inside of networks property. R-MAT can conveniently come up with convincing weighted, directed and bipartite graphs¹³.

PROPOSED Algorithm

The suggested algorithm is actually improved in overall performance than earlier algorithms such as for example gIndex , Part Miner, gSpan & RMat when it comes to of grouping and looking around including DFSS with both left and right connection, graph property with individual dependent query and connection property¹².

That contains the preceding procedures

1. Development of nodes, feature of nodes, and connection between individuals nodes
2. An assortment of property to be explored

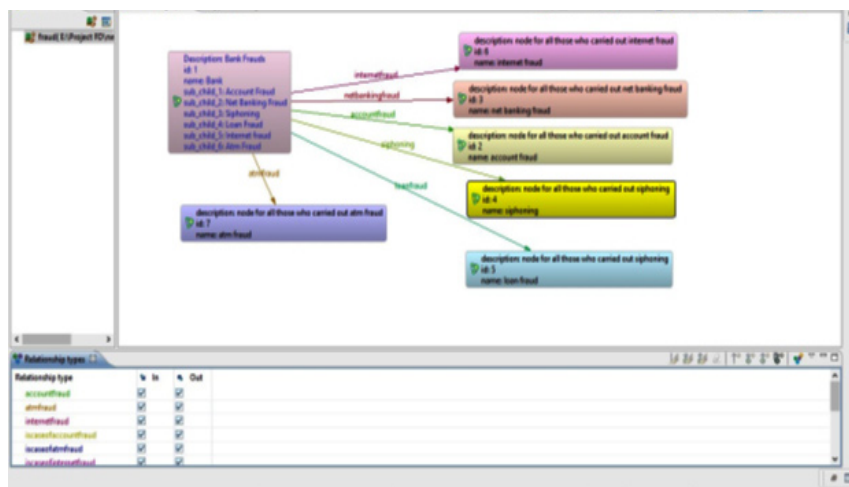


Fig.4: It is showing the information in the form of the graph nodes relationship with bank frauds classified in this system

- and arranging together with the assistance of relationship.
- Traversing towards a specific node which often requires being explored in simultaneously left as well as right way and save the relationship whenever the pattern took place.

Algorithm For Traversing Setup

- Step 1 Create Graph Database
 - Step 2 Create Node
 - Step 3 Set Property of nodes
 - Step 4 Create Relationship
 - Step 5 Select p
- /* Property to be searched */

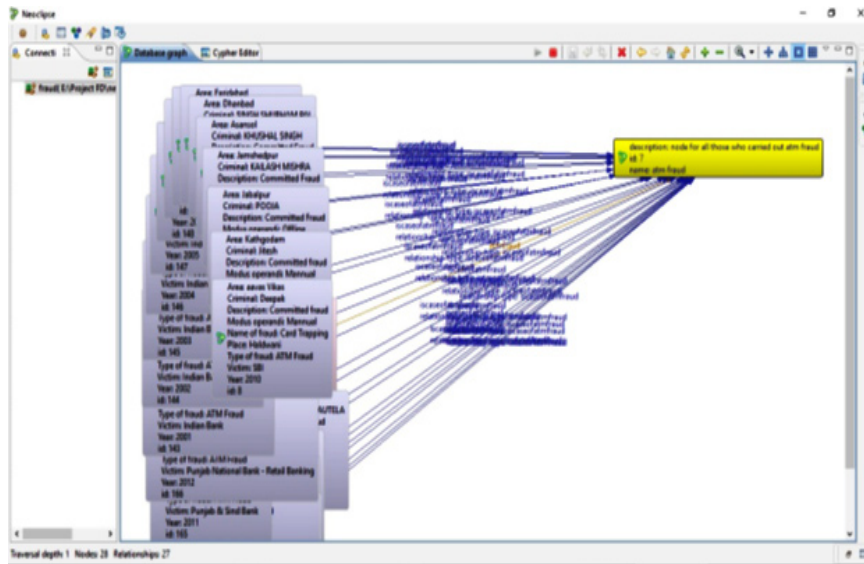


Fig. 5: Displaying the ATM Frauds nodes of classified frauds in this system

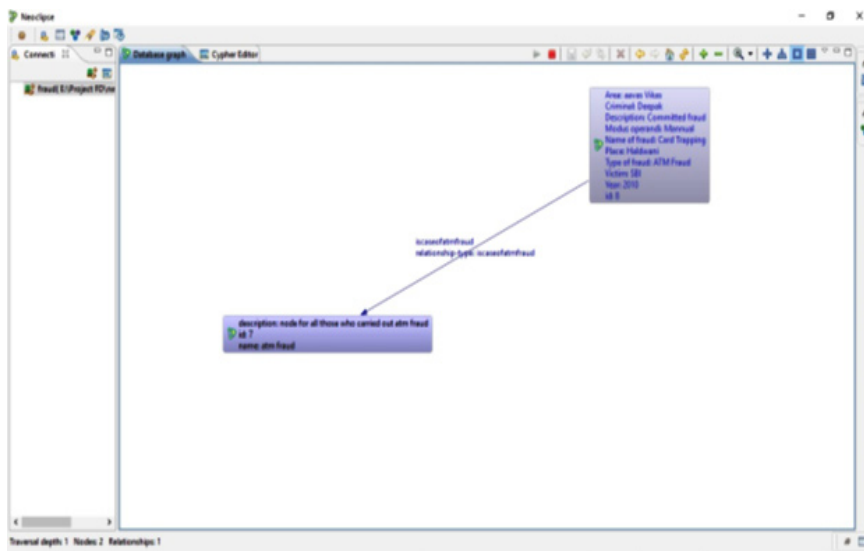


Fig. 6: Demonstrating single ATM Fraud case node of classified frauds in this Database with Node relationship

- | | |
|---|--|
| Step 6 Sort the graph by their relationship | Step 13 else |
| Step 7 for Node position traverse <- depth | Step 14 if node.right.relationship ==S |
| Step 8 if p == node.property | Step 15 Display properties |
| // if required property match | Step 16 continue traverse down |
| Step 9 S <- node-relationship | Step 17 else |
| // store relationship of first match | Step 18 traverse <- down next node |
| Step 10 if node.left.relationship ==S | Step 19 end |
| Step 11 display properties | Step 20 end |
| Step 12 continue traverse down | Step 21 if p==node.property |

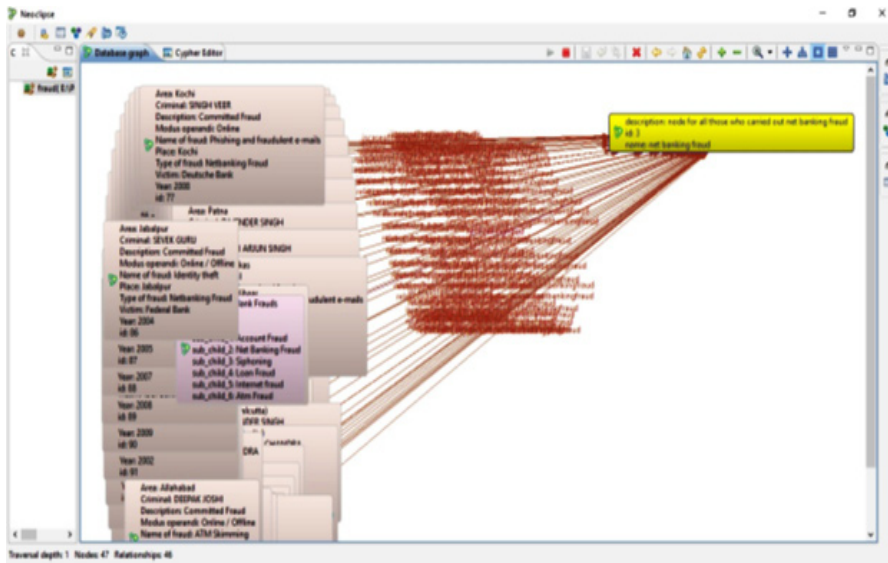


Fig. 7: Displaying the net bank Frauds nodes classified frauds in this system

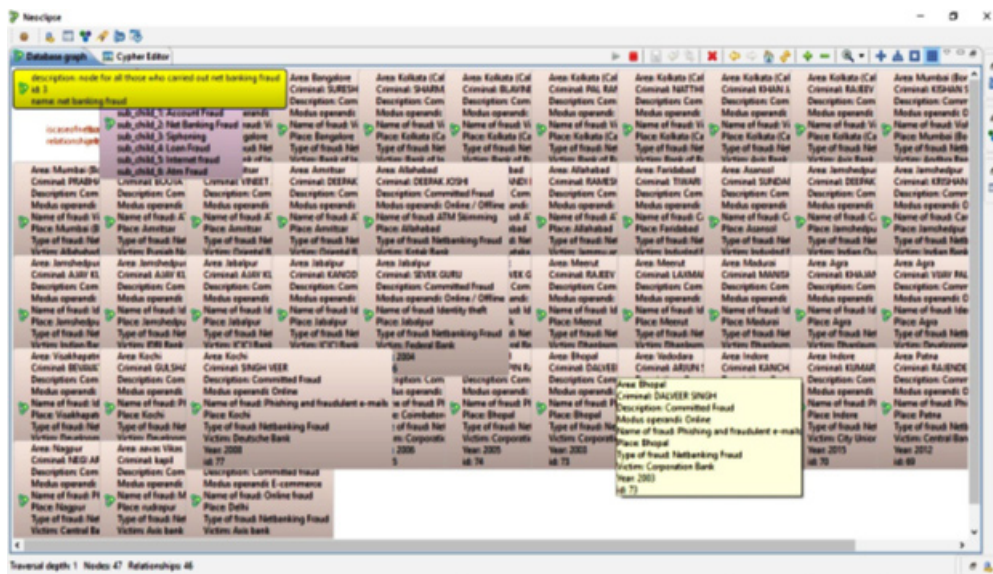


Fig. 8: Displaying different view of graph of net bank Frauds classified frauds in this system

Step 22 repeat
 Step 10 through 18
 Step 23 end
 Step 24 end
 Step 25 end

Comparitive Study & Discussion

The proposed algorithm after reviewed with previously mentioned existing algorithm works amazingly well, it keeps the data in a classified way, seeking happens in both directions left and also right, graph property taking into account client based query furthermore checks the connection whether it is coordinated, one to numerous or many to many relationships. The comparability of existing algorithm with proposed algorithm has appeared in Table 1.

A few snapshots have been taken during the graph database in order to demonstrate the graph database result. At figure 1, 2, 3. it is displaying the result concerning the program code alongside the assorted types of offenses as well as the individuals who are engaging in violations plus beneath it information a few choices is also provided through selecting any of these individuals we can easily obtain the connection of that Fraud that might assist in the upcoming calculation. Summary of graph database production is presented in figure 4. It is demonstrating the name and the information of different types of bank fraud we categorized.

CONCLUSION & FUTURE SCOPE

In spite of the fact that the present algorithm as of now performs entirely well, it can be implemented on a regular basis frameworks to follow the pattern of Fraud ascent and fall in the offer financial sector and we can look at the present graph of financial changes with the pattern present in graph database, so that on the off chance that it finds any similarity in the pattern it can force a security check over that specific transaction and foresee the future progress. This could be helpful in arranging the avoidance of a few wrongdoings which can add to the general population who gets influenced because of fraud. graph mining is a right now exceptionally dynamic research industry. The application zones of graph mining are across the board expanding from science and technology to web applications.

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