Mitigating Insider Threat and Avoiding Unauthorized Knowledge Acquisition Using Acquaintance Based Threat Prediction Graph

Annamma Monisha I* and Grace Selvarani
Department Of Computer Science and Engineering (Pg), Sri Ramakrishna Engineering College, Anna University, Chennai, India

Abstract

An Insider Threat is a malicious threat to an organization it actually comes from people within the organization, such as employees, former employees, contractors or business associates, who have access to the confidential information of the organization. The paper characterizes various types of dependencies as well as constraints on dependencies that may be used by insiders to deduce unauthorized information. It pioneers the constraint and dependency graph (CDG) that characterizes dependencies and constraints. Additionally, CDG shows the paths that insiders can track to acquire unauthorized knowledge. In addition, the paper presents the acquaintance graph (AG) that reveals the knowledgebase of an insider and the amount of information that the insider has about data items. To forecast and prevent insider threat, the paper characterizes and uses the threat prediction graph (TPG). A TPG illustrates the threat prediction value (TPV) of each data item in insiders’ AG, where TPV is used to lift up an alert when an insider threat occurs.

Keywords: Constraints; Dependencies; Threat prediction graph; Acquaintance graph; Knowledge base

Introduction

Security issues are getting more and more critical with the continual use of computers and communication systems. Since data are a vital asset for both individuals and organizations, mechanisms that defend data from interception, modification and invention in such systems have become very serious. One of the major concerns in computer security is the insider threat difficulty. Insider threat is defined as the threat that is reasoned by a malicious insider who has authorized right to use privileges and knowledge of the computer systems of an organization and is encouraged to antagonistically control the organization [1]. Insider threat problem is as important as the problem of outsiders’ intimidation (hackers) due to the excessive harm that it may pose.

According to the Computer Crime and Security Survey, insider attacks accounted for 33% of the total incidents reported in 2010 (C. S. Institute, 2010).

Many mechanisms have been planned for protecting data from outside attacks. However, those mechanisms do not guard data from authorized users who may mishandle their privileges to breach systems security. Thus, developing mechanisms that protect receptive data from insiders has become a key demand due to the amount of harm that can be caused by those spiteful insiders.

Insufficient research has been performed on insider threat in relational databases, such as the work in [2-4]. This paper confers insider threat problem in relational databases. It defines more than a few types of dependencies and constraints that may be used by insiders to get unlawful information. To symbolize dependencies and constraints, the constraint and dependency graph (CDG) is provided. Then, the paper presents a graph-based approach to predict and put off insider threat by using the threat prediction graph (TPG).

The rest of the paper is organized as follows. Related work presents some earlier work which is discussed under heading 4. Types of dependencies are discussed under heading 5. Heading 6 makes obvious the types of constraints on dependencies. Heading 7 Insider Threat: unauthorized knowledge acquisition introduces the problem of gathering unauthorized information by insiders as well as the proposed solutions. Heading 8 presents the conclusions and future work.

Related Work

Insider threat has turned out to be an important security issue due to the tremendous harm [5,6]. Different researchers introduced diverse definitions for insiders at system level, such as [1,7], whereas others defined the insider according to different classes [8]. However, Yaseen and Panda [8-10] defined the insider at the relational databases level, which is the framework of this paper. They defined the insider as a person who has right to use privileges, is familiar with dependencies and their constraints and is familiar with the system under contemplation.

Researchers used existing methods of detecting external threat, such as using honeypots [11], to sense insider threat. However, these methods are not efficient since insiders and outsiders use diverse paths or advancements to attack systems. In other terms, insiders use their right to use privileges and knowledge about systems to harass sensitive data items using paths that are hard to be detected by security mechanisms, while outsiders use arbitrary paths that lead to perceptive and insensitive data items, where these paths can be detected by well-arranged security mechanisms. Other researchers such as [7] initiated new methods to deal with this problem. They introduced a new acquaintance base approach to notice and prevent insider threat. However, the aforesaid research was at the system level and did not consider relational databases, where insiders have more means such as the knowledge about dependencies and constraints that facilitate start on attacks.

*Corresponding author: Annamma Monisha, Department of computer science and engineering (PG), Sri Ramakrishna engineering college, Anna University, Chennai, India, Tel: 0422 246 1588; E-mail: monishaimmans@gmail.com

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Jabbour and Menasce [12,13] proposed a self-protection mechanism, which is the Insider Threat Security Architecture (ITSA), that is totally incorporated into the computing system. However, their self-protection mechanism has scalability problems that may abort the performance of hosting systems and influence other services. Moreover, their approach seems to be tested and estimated to ensure its effectiveness and applicability in diverse environments.

Dependencies in relational databases play a most important role in insider threat problem. Dependencies as well as the inference problem have been conversed extensively in [14]. Farkas, and Jajodia [14] and Farkas et al. [14] discussed how users can get receptive data using non sensitive data to which they have no right to use. Yaseen and Panda [8-10] discussed the outcome of changing the value of one of them depends on the value of the other. A threat in relational databases.

Knowledgebase of insiders and the lifetimes of data items on insider threats in this paper. Yaseen and Panda [8-10] discussed the outcome of an update to all granularity levels. The final constraint is represented by $a1 \rightarrow a2 \rightarrow c3$, $(a1 \rightarrow a2 \rightarrow c4)$, $(a4 \rightarrow 2^a3 + 3)$, $(a6 \rightarrow 2^a2 + 2^a5)$). Figure 1 illustrates the CDG of this relational data base using Petri Nets. Every attribute is represented by a circle, and a dependency is symbolized by an edge (arrow) from the source attribute (left side) to the target attribute (right side). Constraints are placed on top of bars. For example, to vary the value of the attribute $a2$ in table $T1$ to $c4$, the value of the attribute $a1$ in table $T1$ should be set to a value less than $c1$. The final constraint is represented by writing $(T1 \cdot a1 < c1)$ above the transition (bar). Note that each attribute is headed by the table to which it belongs, which expands the possible use of CDG to all granularity levels.

The CDG characterizes the constraints of the first type. To illustrate both types of constraints at the table level (and implicitly the record level), the Dependency Matrix is used. Table 1 symbolizes an example.
of a Dependency Matrix that shows dependencies between different tables as well as the constraints on such dependencies. The first row and first column Characterize tables. Every cell contains a set of pairs \((C, T)\), where \(C\) denotes a constraint, and \(T\) indicates the type of the dependency. The value 2 means a strong dependency, while the value 1 means a weak dependency.

Insider threat: Unauthorized Knowledge Acquisition

This section reveals how insiders can get unauthorized information and widen their knowledge bases using dependencies and constraints. Additionally, it discusses approaches for predicting and preventing such threats.

Insiders knowledge bases (KBs)

Acquaintance base (AB) decides which data items a insider has read. Actually, it is a profile of insider accesses to data items. Knowledgebase is raised based on the several levels of granularities of relational databases.

To calculate how much information the insider has about specific attributes, the NIDG [3] is used. The Neural Dependency and Inference Graph \((D,N,W,E)\) (NIDG) gives you an idea about dependencies among relational database data items and the amount of information that can be inferred regarding them using dependencies, where \(D\), \(N\), \(W\) and \(E\) indicate data items, neurons, weights on edges and edges, correspondingly. Figure 2 gives you an idea about an example of the NIDG of the database in Figure 1, where data items are symbolized by rectangles and neurons are represented by circles. Arrows symbolize dependencies, where the destination data item depends on the source data item. Weights on edges give details about the amount of information that can be inferred about destination data items using the source data items. For instance, the attribute \(a_2\) alone can be used to infer 60% of information about \(a_6\). On the other hand, \(a_2\) and \(a_5\) can be used jointly to infer 100% of information about \(a_6\). These values are calculated by calculating the uncertainty of the value of a destination data item with and without getting the value of source data item(s). For instance, the uncertainty of the letter grade of a student in a course is 5 since the possible values are \(A, B, C, D\) and \(F\). Nevertheless, without loss of generalization, with getting the Score of the student, the improbability of the letter score is 0 since, in this case, the letter grade is calculated exactly. Next, the amount of information that can be obtained about the letter grade given the Score is computed as follows: \((5−0)/5 = 100\%\).

Acquaintance algorithm

Algorithm 1 demonstrates the algorithm for building the acquaintance graph, which symbolizes knowledgebase (KB) at several levels of granularity. It makes use of the NIDG as well as CDG of the relational database beneath consideration as well as the Dependency Matrix. The algorithm appends the insider as a root of the knowledge graph. The second level of the graph encloses the tables to which the insider has read right (directly or by inference) (Figure 3). For every table in the second level, the algorithm decides to which attributes the insider has read access. The NIDG is used to tag edges by the amount of information the insider can have about apiece data item (attribute or
NDIG or CDG is used to show dependencies between knowledge units (attributes), which are corresponded by an edge (arrow) from the source attribute to the destination (dependent) attribute. Additionally, the CDG is used to show what values of attributes are accumulated in the KB of the corresponding insider as mentioned earlier, which is used in insider threat predicting and preventing later in Insider threat prediction and prevention. Note that the amount of information the insider has about a table is the standard of all information she/he has about all attributes belonging to the Table 1.

Algorithm 1: Acquaintance base (AB) Algorithm

Input: An insider I. Dependency Matrix, CDG, NDIG, Set of tables that insider has direct read access.

Output: The Acquaintance graph of the insider I.

1. Initialize the AG=(V,E), where V=I, E={}, and insider I.
2. For each table Tk in D, add directly accessed tables
3. \( V=V \cup T_k \) // add the table T_k to AG
4. \( E=E \cup \{I, T_k\} \) // add the edge e(I, T_k) to the AG
5. For each t \( \in \) attributes(T_k) and the insider has a read-access to it, add directly accessed attributes
6. \( V=V \cup t \) // add the attribute t to AG
7. \( E=E \cup \{I, T, t\} \) // add edge e(I, T, t) to the AG
8. Endfor

9. For each table T_k in D do, consider dependencies
10. For each Safe cluster R to which T_k belongs
11. \( V=V \cup R \) // add the node R to AG
12. \( E=E \cup \{I, R\} \) // add the edge e(I, R) to the AG
13. Endfor
14. For each Hot cluster H to which T_k belongs
15. \( V=V \cup H \) // add the node H to AG
16. \( E=E \cup \{I, H\} \) // add the edge e(I, H) to the AG
17. Endfor
18. For each t \( \in \) attributes(T_k) \( \land \) t \( \in \) attributes(T_s)
19. \( V=V \cup t \) // add the attribute t to AG
20. \( E=E \cup \{I, T, t\} \) // add edge e(I, T, t) to the AG
21. Endfor

22. For each table T_j that depends transitively on T_k
23. \( V=V \cup T_j \) // add the table T_j to AG
24. \( E=E \cup \{I, T_j\} \) // add the edge e(I, T_j) to the AG
25. \( V=V \cup T_k \) // add the table T_k to AG
26. \( E=E \cup \{I, T_j, T_k\} \) // add edge e(I, T_j, T_k) to the AG
27. Endfor

28. For each t \( \in \) attributes(T_s) \( \land \) t \( \Rightarrow \) t \( \text{(direct dependency)} \)
29. \( V=V \cup t \) // add the directly inferred attribute(s) to AG
30. \( E=E \cup \{I, T, t\} \) // add edge e(I, T, t) to AG
31. \( E=E \cup \{I, T_s, t\} \) // add edge e(I, T_s, t) to AG
32. Endfor

33. Endfor
34. For each table T_j that depends transitively on T_k
35. \( V=V \cup T_j \) // add the table T_j to AG
36. \( E=E \cup \{I, T_j\} \) // add edge e(I, T_j) to AG
37. For each t \( \in \) attributes(T_j) \( \land \) t \( \Rightarrow \) T_k \( \text{(transitive dependency)} \)
38. \( V=V \cup T_k \) // add the transitively inferred attribute(s) to AG
39. \( E=E \cup \{I, T_j, T_k\} \) // add edge e(I, T_j, T_k) to AG
40. \( E=E \cup \{I, T_j, T_k\} \) // add edge e(I, T_j, T_k) to AG
41. Endfor
42. Endfor
43. Endfor
44. For each edge e(I, T) \( \in \) AG // is a table and t is an attribute
45. Weight \( (e(T_i)) = \) the amount of information the insider has about t // weights of attributes using NDIG
46. Endfor
47. For each edge e(I, T) \( \in \) AG // weights of tables
48. Weight \( (e(I, T)) = \) \[ \sum_{i=1}^{n} \text{Weight (e(T_i, t_i))} / n \]

where n is the number of attributes in T.

49. Endfor

Insider threat prediction and prevention

Building the knowledge graph of an insider assists in predicting and preventing insider threat (revelation of unauthorized information). To attain this goal, the threat prediction graph (TPG) is used, which is built based on the knowledge graph. Previous to defining the TPG properly, let us introduce the threat prediction value (TPV). A TPV is a value stock up in each attribute that belongs to the TPG of the insider and used to foresee inside threat. A TPG is calculated as follows:

\[ \text{TPV} (k) = f(k)/T (k) \] (1)

Where k is an attribute, f(k) is the amount of information the insider has about k, and T(k) is the threshold value of k (the amount of information that the insider is permitted to get about k) according to the insider under deliberation. The TPG uses TPV to sense and prevent insider threat.

Figure 4 shows an instance of a TPG. The NDIG, the AG and the set of threshold values according to the underlying insider are used to
construct the TPG. A threshold value of an attribute according to an insider represents the percent amount of information that the insider is allowed to get about the data item. 100% indicates that the insider can get full information about the data item, and values less than that indicate that the insider can get partial information about the data item.

As discussed earlier, the amount of information that an insider gets about a data item is retrieved using the NDIG.

Algorithm 2: TPG Algorithm

**Input:** An insider I, the set of threshold values according to the insider, NDIG, the acquaintance graph AG of the insider.

**Output:** The Threat Prediction Graph TPG of the insider I.

1. Initialize the set of pairs T={(KU,TKU)}, where TKU is the threshold value about a knowledge unit KU according to the insider I, an empty set S={}
2. Recall the AG of the insider and the NDIG, initialize the TPG as TPG=AG, but without labels
3. For each KU ∈ V(TPG) is a knowledge unit and Vis the set of vertices
4. TPV(KU)=f(KU)/T(KU) compute the TPV of KU
5. Endfor
6. For each requested knowledge unit RKU by the insider
7. If TPV(RKU)>1 threat predicted
8. Deny this request
9. Else add RKU temporarily for further inspection
10. V=V∪{RKU} add a node for RKU
11. E=E∪{e(I, RKU)} add an edge to the TPG
12. TPV(RKU)=f(RKU)/T(RKU)
13. For each knowledge unit KUx that has a dependency with the RKU add inferred attributes
14. If TPV(KUx)>1 threat predicted
15. Deny RKU and remove it from TPG
16. Else no threat so far, still needs further inspection
17. If KUx∉V not in the TPG
18. If KUx and RKU are not in the same table add inferred attributes
19. V=V∪{RKU} add a node for RKU
20. E=E∪{e(I, RKU)} add an edge to the TPG
21. TPV(RKU)=f(RKU)/T(RKU)
22. Else
23. V=V∪{RKU} add a node for RKU
24. E=E∪{e(RKU, KUx)} add an edge
25. TPV(RKU)=f(RKU)/T(RKU)
26. Endif
27. V=V∪{RKU} add a node for RKU
28. E=E∪{e(RKU, KUx)} add an edge
29. TPV(RKU)=f(RKU)/T(RKU)
30. Endif
31. Else If KUX∉V already in the TPG
32. Add KUX to the set S
33. E=E∪{e(RKU, KUX)} add an edge to the TPG
34. Update the TPV of KUX recalibrate its TPV
35. Endif
36. Endif
37. Endfor
38. For each KU in S
39. If TPV(KU)>1 threat predicted
40. then there are two choices threat prevention
41. First Grant access to RKU but revoke access to a knowledge unit(s) that has the following three properties:
   (a) It already exists in the knowledgebase of the insider.
   (b) Can be used in conjunction with RKU to compromise unauthorized information about KU.
   (c) The lifetime of the knowledge unit(s) is expired.
42. Second Do not grant access to the RKU and copy the TPG initialized in steps 2-6 and restore it here.
43. Endif
44. Endif

![Figure 4: Threat prediction graph.](image)
Algorithm 2 shows the algorithm for detection and prevention of insider threat using TPG. In this algorithm, a knowledge unit KU represents an attribute. A knowledge unit is considered a threat if its TPV is greater than one.

Results and Discussion

Insider threat has become an imperative security issue to the organizations confidential information. Different researchers introduced different characterizations for insiders at system level, whereas others defined the insider according to different classes. Nevertheless, this system defines the insider at the relational database level. They termed the insider as a person who has access privileges, is familiar with dependencies and their constraints and is recognizable with the system under consideration. Some researchers used existing methods of detecting outside threat, such as using honeypots, to detect insider threat. However, these methods are not efficient since insiders and outsiders use different corridors or approaches to attack systems.

Other researchers introduced new methods to deal with this dilemma. They introduced a new knowledge base loom to detect and prevent insider threat. Nevertheless, most of the research was at the system level and did not reflect on relational databases, where insiders have more capabilities such as the knowledge about dependencies and constraints that make possible launching attacks.

Jabbour and Menascé [12,13] suggested a self-protection mechanism, which is the Insider Threat Security Architecture (ITSA) [7] that is totally integrated into the computing system. Nevertheless, their self-protection mechanism has scalability problems that may put down the performance of hosting systems.

Dependencies in relational databases play a major role in insider threat problem. The proposed system addresses the insider threat in relational databases and developed the Neural Dependency and Inference Graph (NDIG), which demonstrates the dependencies amongst data items and the amount of information that can be deduced about data items using dependencies. The system also shows the Knowledge base graph produced based on the Knowledge base algorithm. The Knowledge base graph demonstrates the amount of information that the insider has regarding data items.

To forecast and avoid insider threat, the system defines and uses the threat prediction graph (TPG). A TPG demonstrates the threat prediction value (TPV) of each data item in insiders AG, where TPV is used to lift up an alert when an insider threat occurs, where other methods do not use this approach to prevent the threat.

The graph in Figure 5 shows the relation between different insiders and their access level. The graph also shows the declining right to use level of the insider 1 due to the threat he possesses.

Conclusion and Future Work

The proposed system has investigated the problem of insider threat in relational database systems. It has considered different levels of granularities of data items and identified various types of dependencies. Moreover, it has shown how insiders who have knowledge about dependencies may infer information about unauthorized data items. Additionally, the paper has explained how constraints on dependencies play an important role in knowledge acquisition. It has introduced the constraint and dependency graph (CDG) and the Dependency Matrix these data structures show diverse types of dependencies and constraints in relational database systems. An algorithm for constructing insider’s knowledgebase has been provided. The algorithm helps in building the knowledgebase of an insider and determines the data items which the insider can access in unauthorized way. Moreover, the paper has defined the threat prediction graph (TPG), which is used to predict and prevent insider threat. An algorithm for predicting and preventing insider threat has been stated. As a future work, the recommended system has been planned to expand the proposed approaches to general access control systems.

References