

Strategies for Knowledge Based Attack Detection in Graphical Data Anonymization

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Abstract: Recent years have seen a rapid growth in web applications developed, which gave rise to the increasing need for private data to be published. Most of the social network data necessitates the data to be available for easy access and conversion of data to graph structure to re-identify sensitive labels of individuals became an impeccable issue. Privacy protection scheme that not only prevents the disclosure of identify of users but also the disclosure of selected features in users' profile. Existing KDLD (k-degree l-diversity) model for ensuring anonymity of data, have some restrained but severe privacy problems. Firstly, an attacker can discover the values of sensitive attributes when there is little diversity in those sensitive attributes leading to homogeneity attack. Secondly, an adversary could often use background knowledge to discover sensitive information, causing a background knowledge attack. Thirdly, when the sensitive attribute values in an equivalence class are distinct but semantically similar, an adversary can learn important information, rooting to the problem of similarity attack. This paper considers the problem of detecting these three attacks in a k-degree-l-diversity (KDLD) graph based data and to address the same on graphical data.

Keywords: Privacy, Graphical Data, Re-identification, Attack, Data Security, Anonymization

I. INTRODUCTION

Need for publishing sensitive data to public has grown extravagantly during recent years. Though publishing demands its need there is a restriction that published social network data should not disclose private information of individuals. Hence protecting privacy of individuals and ensuring utility of social network data as well becomes a challenging and interesting research topic. Considering a graphical model [35] where the vertex indicates a sensitive label algorithms could be developed to publish the non-tabular data without compromising privacy of individuals. Though the data is represented in graphical model after KDLD sequence generation [35] the data is susceptible to several attacks such as homogeneity attack, background knowledge attack, similarity attacks and many more. In this paper we have made an investigation on the attacks and possible solutions proposed in literature and efficiency of the same.

The remainder of the paper is organized as follows. Techniques for detecting abnormal graph structures are dealt in detail in Section 2. Section 3 gives the survey on attacks on social network data. Section 4 briefs about techniques to prevent and handle the attacks on social network data. The problem description is outlined in Section 5. The attack scenarios on KDLD based sequence data is dealt in Section 6. Section 7 describes the results and discussions. Section 8 concludes the paper and outlines the future work.

II. TECHNIQUES FOR DETECTING ABNORMAL STRUCTURES IN GRAPHS

W. Eberle and L. Holder(2007)[9] dealt in detail about discovering structural anomalies in graph-based data. Authors presented graph-based approaches to expose anomalies in domains where the anomalies consist of entity/relationship alterations that closely resemble non-anomalous activities. Further they introduced three new

algorithms for detecting anomalies in all three types of possible graph changes namely label modifications, vertex/edge insertions and vertex/edge deletions. Each of the three proposed algorithms focuses on one of these anomalous types and uses the minimum description length principle to discover those substructure instances that contain anomalous entities and relationships. Authors evaluated the effectiveness of each of these algorithms in terms of each of the types of anomalies using synthetic and real-world data for the purposes of detecting fraud.

C.C. Noble and D.J. Cook (2003) [22] dealt about graph-based anomaly detection. Authors introduced two techniques for graph-based anomaly detection. In addition, a new method for calculating the regularity of a graph, with applications to anomaly detection was also proposed. Authors hypothesized that these methods established usefulness for finding anomalies, and for determining the likelihood of successful anomaly detection within graph-based data. The work was supported with experimental results generated using both real-world network intrusion data and artificially-generated data.

III. ATTACKS ON SOCIAL NETWORK DATA

There's another type of attack on social networks, which is called "active attack." "Active attack" (2013) [35] is to actively implant special subgraphs into a social network when this social network is collecting data. An attacker can attack the users who are connected with the embedded subgraphs by reidentifying these special subgraphs in the published graph. Backstrom et al.(2007) [1] described active attacks based on randomness analysis and showed that an attacker may fix some constructed substructures linked with the target entities. One technique to stop the active attack is to distinguish the fake nodes appended by attackers and eliminate them before releasing the data. Authors also described a set of attacks such that even from

a single anonymized version of a social network, it is possible for an adversary to gain knowledge whether edges exist or not between explicit targeted pairs of nodes.

Shrivastava et al. [25] and Ying et al. [28] threw light on a special active attack named Random Link Attack. Shrivastava et al. [25] projected an algorithm that is capable of identifying fake nodes based on the triangle probability difference between normal nodes and fake nodes. Ying et al. [28] proposed an alternate method, which employs spectrum analysis to identify the fake nodes. To publish a graph that is potentially changed by Random Link Attack, the publisher can employ a twostep mechanism proposed by the authors. First, the graph is filtered by the methods introduced by Backstrom et al. [1] or Shrivastava et al. [25]. Second, the attacker can produce the published graph using the proposed model from the filtered graph.

X. Ying, X. Wu, and D. Barbara (2011) [28] worked on spectrum based fraud detection in social networks. Since social networks are susceptible to a variety of attacks such as spam emails, viral marketing etc., the authors developed a spectrum based detection framework to discover the perpetrators of these attacks. In specific, the authors focused on Random Link Attacks (RLAs) in which the malicious user introduces multiple false identities and interactions among those identities to later proceed to attack the regular members of the network. Through experimental results authors proved that RLA attackers can be filtered by using their spectral coordinate characteristics, which are hard to hide even after the efforts by the attackers of mimicking as much as possible the entire network, and the proposed method is found to be promising in detecting those attackers and outperforms various other techniques in the literature.

There are also two other works in literature that focus on the edge weight protection in weighted graphs. Liu et al. [19] treated weights on the edges as sensitive labels and proposed a method to preserve shortest paths between most pairs of nodes in the graph. L. Liu, J. Wang, J. Liu, and J. Zhang (2008) [19] considered preserving weights data privacy of certain edges, while trying to preserve close shortest path lengths and exactly the same shortest paths of certain pairs of nodes. Also the authors developed two privacy preserving strategies for this application. The first strategy is based on a Gaussian randomization multiplication, and the second one is a greedy perturbation algorithm which is based on the graph theory.

Das et al. [8] proposed a Linear Programming-based method to protect the edge weights while preserving the path of shortest paths. These two works focused on the protection of edge weights instead of nodes. Some authors studied other attacks besides the “passive attack” and “active attack.” Zheleva [31] analyzed the ability of an attacker to learn the unpublished attributes of users in an online social network when the user uses the published attributes and relationships between users to do the data mining. E. Zheleva and L. Getoor (2009) [31] studied the illusion of privacy in social networks with mixed public and private user profiles. Authors depicted how an

adversary can exploit an online social network with a mixture of public and private user profiles to predict the private attributes of users. This problem is mapped to a relational classification problem and authors proposed practical models that use friendship and group membership information to infer sensitive attributes. Authors' key novel idea is that in addition to friendship links, groups can be carriers of significant information. They proved that on several well-known social media sites, the information regarding private-profile users can easily and accurately be recovered. the information of private-profile users.

Narayanan and Shmatikov [21] (2009) proved the fact that from “seed nodes,” a large quantity of other nodes can be reidentified. Authors aimed to develop effective algorithms for de-anonymizing real-world social networks. In specific, authors focused on dual tasks: one is to align the networks of Flickr and Instagram and the other is to align Flickr and Twitter. Their work was motivated by the two parts of information that network data is composed of: network structure and node attributes. Preliminary tests conducted by the authors proved that de-anonymizing algorithm based merely on node attributes, is computationally effective but not adequately accurate. As against, algorithms that rely on network structures, which bring in more relationship information, might contribute to the precision of de-anonymization. Authors concluded that the structure of the real-world social networks be quite different, but also the computation costs will be significantly high because it is difficult to align two networks merely based on their structures without any assisting information. With these facts, authors decided to develop approaches that can combine network structure information and node attributes to do the alignment.

L. Page, S. Brin, R. Motwani, and T. Winograd (1999) [23] describes PageRank method for rating Web pages objectively and mechanically, effectively measuring the human interest and attention devoted to them. Authors compared PageRank to an idealized random Web surfer and illustrated techniques to efficiently compute PageRank for large numbers of pages and to apply PageRank to search and to user routing. S.R.Ganta, S. Kasiviswanathan, and A. Smith (2008) [11] explored how an individual can reason about privacy in the presence of concrete sources of auxiliary information. Specifically, the authors investigated the effectiveness of current anonymization schemes in preserving privacy when multiple organizations independently release anonymized data about overlapping populations. Further investigations were also carried out by the author in composition attacks, in which an adversary uses independent anonymized releases to violate privacy. Authors clarify the reason behind the failure of recently proposed models of limited auxiliary information to capture composition attacks. For the proposed technique, authors demonstrated that even a simple instance of a composition attack can breach privacy. Optimistically, some randomization-based notions of privacy, usually resist composition attacks and, in fact, the use of arbitrary side information. This resistance allows “stand-alone” design of anonymization

schemes, eliminating the need for explicitly keeping track of other releases. Authors also provide an accurate formulation of this property, and proved that an important class of relaxations of differential privacy also satisfy the property.

Zou et al. (2009) [34] proposed k-automorphism to protect against multiple structural attacks and develop an algorithm called KM that ensures k-automorphism. Authors also discussed an extension of KM to handle “dynamic” releases of the data. A graph is k-Automorphism if and only if for every node there exist at least k-1 other nodes do not have any structure difference with it. Extensive experiments prove that k-automorphism performs well in terms of protection. J.Cheng, A.W.c. Fu, and J. Liu (2010) [6] identified a new problem of enforcing k-security for protecting sensitive information concerning the nodes and links in a published network dataset. Their investigation lead to the invention of k-isomorphism where, the selection of anonymization algorithm depends on the adversary knowledge and the targets of protection. Authors addressed the information of protection against structural attack if the target is only NodeInfo. Authors say that NodeInfo and LinkInfo are two basic sources of sensitive information in network datasets, and they call for special efforts for their security. X. Xiao and Y. Tao (2006) [27] developed a linear-time algorithm for computing anonymized tables that obey the l-diversity privacy requirement, and diminish the fault of reconstructing the microdata. Extensive experimental results of the authors confirm the fact that the proposed technique allows significantly more effective data analysis than the conventional publication method based on generalization. Especially, anatomy allows aggregate reasoning with average error below 10%, which is lower than the error obtained from a generalized table interms magnitude.

X. Ying and X. Wu (2008) [29] proposed a spectrum preserving approach of randomizing social networks. Authors investigated the consequence of various properties of networks due to randomization. They studied how random deleting and swapping edges change graph properties and proposed an eigenvalues oriented random graph change algorithm. All the edge editing- based models prefers to produce a published graph with as fewer edge change. A. Campan and T.M. Truta (2008) [4] proposed a clustering approach for data and structural anonymity in social networks. Authors discussed how to implement clustering when considering the lost of both node labels and structure information S.Bhagat, G. Cormode, B. Krishnamurthy, and D. Srivastava (2009) [3] enunciated a Class based graph anonymization for social network data. Since social network data is more affluent in details about the users and their communications, loss of details due to anonymization confines the possibility for analysis. Authors present a new set of techniques for anonymizing social network data based on grouping the entities into classes, and masking the mapping between entities and the nodes that represent them in the anonymized graph. Their techniques allow queries over the rich data to be evaluated with high degree of accuracy

while guaranteeing flexibility to certain types of attack. To prevent inference of interactions, there is a support on a critical “safety condition” when forming these classes. Authors demonstrate utility via empirical data from social networking settings and provide illustrations of complex queries that may be posed and proved that they can be answered over the anonymized data more efficiently and effectively.

IV. TECHNIQUES TO PREVENT AND HANDLE THE ATTACKS ON SOCIAL NETWORK DATA

K. Liu and E. Terzi (2008) [18] formally defined the graph-anonymization problem and devise simple and efficient algorithms for solving the problem. The algorithms are based on principles related to the realizability of degree sequences. The algorithms were applied to a huge range of synthetic and real datasets and their efficiency and practical utility is demonstrated. B.Zhou and J. Pei (2008) [32] identified a type of privacy attacks called neighborhood attacks. If an antagonist has certain knowledge about the neighbors of a target prey and the relationship among the neighbors, the prey may be re-identified from a social network even if the prey’s identity is preserved by employing conventional anonymization techniques. They also proved that the problem is challenging and NP-hard and gave a practical solution to fight against neighborhood attacks. The empirical study indicated that their method of generation of anonymized social networks can be employed to answer aggregate network queries with peak accuracy.

M. Hay, G. Miklau, D. Jensen, D. Towsley, and P. Weis (2008) [15] categorized the entities connected by relations such as friendship, communication, or shared activity. They quantified the privacy risks associated with three different classes of attacks on the privacy of individuals in networks, based on the adversarial knowledge. They proved that network structure and size are the main root of the risks of these attacks. They also proposed a novel approach to anonymizing network data that models aggregate network structure and then allows samples to be drawn from that model, which guarantees anonymity for network entities while preserving the ability to estimate a wide variety of network measures with negligible bias.

L. Zou, L. Chen, and M.T. Ozsu (2009) [34] proposed k-automorphism to protect against multiple structural attacks and developed an algorithm called KM that ensures k-automorphism. Authors also discussed an extension of KM to handle “dynamic” releases of the data and proved that the algorithm performs well in terms of protection it provides. A significant work of defining a k-degree anonymity model to prevent degree attacks that employ node degree is done by Liu and Terzi (2008) [18]. A graph is termed to be k-degree anonymous if and only if for every node in the graph, there exist at least k-1 other nodes with the same degree

V. PROBLEM DESCRIPTION

Three attacks that a k-degree l-diversity graph based data have that cause some restrained but severe privacy problems.

- First, an attacker can discover the values of sensitive attributes when there is little diversity in those sensitive attributes. This attack is known to be the homogeneity attack.
- Secondly, an adversary could often use background knowledge to discover sensitive information. This attack is termed to be background knowledge attack.
- Thirdly, when the sensitive attribute values in an equivalence class are distinct but semantically similar, an adversary can learn important information. This attack is termed to be similarity attack.

In literature there are techniques to detect these three attacks on tabular data. Consider the problem of detecting the three attacks namely homogeneity, background knowledge and similarity attack for a KDLD based graph based data is addressed. To achieve this goal, define a k-degree-l-diversity (KDLD) model for safely publishing a labeled graph, and then develop corresponding graph anonymization algorithms with the least distortion to the properties of the original graph, such as degrees and distances between nodes and then address the detection of each of these attacks on graphical data.

VI. ATTACK SCENARIOS ON KDLD BASED SEQUENCE DATA

Even though noise nodes are constructed to increase and decrease the degree changes the possibility some attacks in graphical data still persists. Attack scenarios include

- Homogeneity Attack
- Background knowledge Attack
- Similarity Attack

(i) Homogeneity Attack

Assume Alice and Bob are antagonistic neighbours. One day Bob falls ill and is taken by ambulance to the hospital. Having seen the ambulance, Alice sets out to discover what disease Bob is suffering from. Alice discovers the 4-anonymous table of current inpatient records published by the hospital (Fig 1), and so she knows that one of the records in this table contains Bob's data. Since Alice is Bob's neighbour, she knows that Bob is a 31-year-old American male who lives in the zip code 13053. Therefore, Alice knows that Bob's record number is 9,10,11, or 12. Now, all of those patients have the same medical condition (cancer), and so Alice concludes that Bob has cancer

(ii) Background Knowledge Attack

Considering the scenario that Alice has a pen- friend named Umeko who is admitted to the same hospital as Bob, and whose patient records also appear in the table shown in Fig 1. Alice knows that Umeko is a 21 year- old Japanese female who currently lives in zip code 13068. Based on this information, Alice learns that Umeko's information is contained in record number 1,2,3, or 4. Without additional information, Alice is not sure whether Umeko caught a virus or has heart disease. However, it is well- known that Japanese have an extremely low incidence of heart disease. Therefore Alice concludes with near certainty that Umeko has a viral infection.

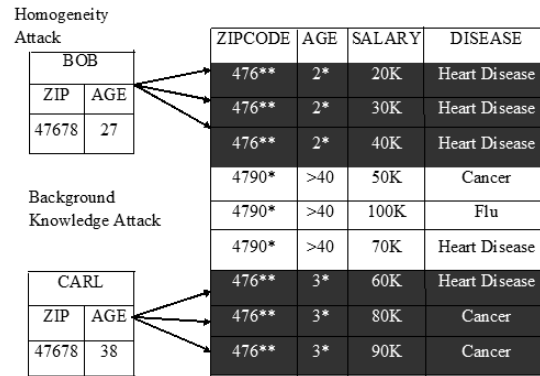


Fig 1. Schematic Diagram of Homogeneity Attack and Background Knowledge Attack

(iii) Similarity Attack

From the example given above, the sensitive attributes are Salary and Disease. If Alice knows Bob has a low salary (20k-40k) also she knows that he has a stomach related disease and she can easily found the disease of Bob. This is because l-diversity takes into account the diversity of sensitive values in the group, but does not take into account the semantical closeness of the values. The fact is illustrated in Fig 2

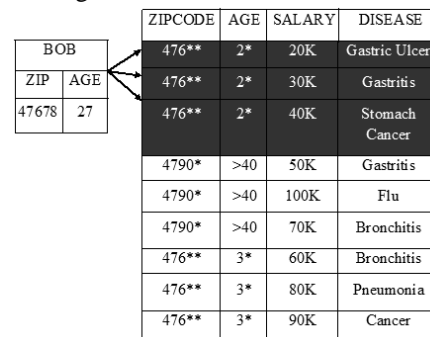


Fig 2. Schematic Diagram of Similarity Attack

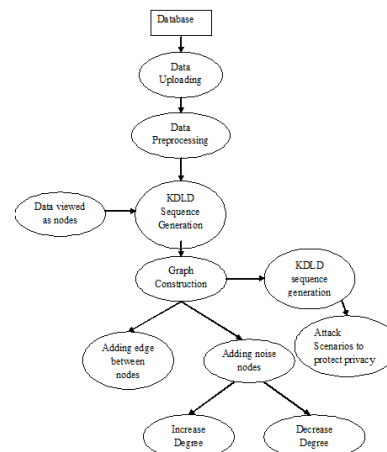


Fig 3. Data Flow Diagram for KDLD Sequence Generation and Attack Detection Scenarios

A idea to preserve important graph properties, such as distances between nodes is by adding certain "noise" nodes into a graph. In proposed work, privacy preserving aims to prevent an attacker from reidentifying a user and finding the fact that a certain user has a specific sensitive value. To achieve this goal, k-degree-l-diversity model is adapted for safely publishing a labelled graph, and then

develop corresponding graph anonymization algorithms with the least distortion to the properties of the original graph, such as degrees and distances between nodes. k-degree anonymity with l-diversity is combined to prevent not only the reidentification of individual nodes but also the revelation of a sensitive attribute associated with each node. Despite the fact that noise nodes are constructed to increase and decrease the degree changes the possibility some attacks such as homogeneity attack, background knowledge attack and similarity attack in graphical data still persists. Strategies are designed to detect the above said attacks in graph based data structure. The functional flow is illustrated in Fig 3.

VII. RESULTS AND DISCUSSION

Homogeneity attack, background knowledge attack and similarity attack are detected in graphical data with a clustered data as input. The initial cluster is subject to scanning for quasi identifier values for homogeneity and background knowledge attack detection. With the knowledge of the semantic relationship among values of sensitive attributes and quasi identifiers, the detection strategy is designed for similarity attack. The attack detection scenarios are implemented and tested in a Dell Laptop with Intel Core i5 Pentium IV CPU with 6 GB RAM and 64-bit Windows XP OS. The algorithm is implemented in Netbeans IDE 6.9.1 with MySQL as backend.

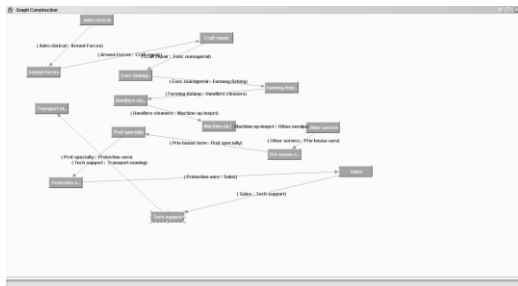
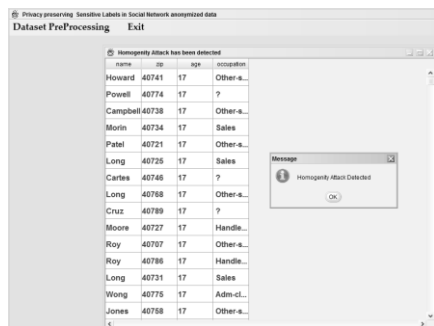


Fig 4. Initial Graph Construction with Sensitive Labels

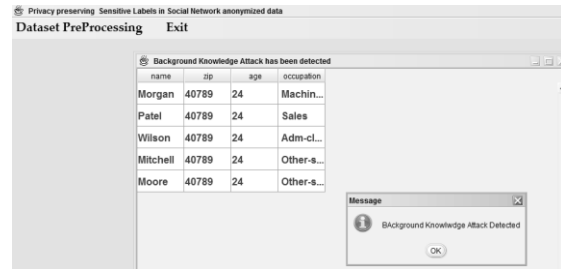


name	zip	age	occupation
Howard	40741	17	Other-s...
Powell	40774	17	?
Campbell	40738	17	Other-s...
Morin	40734	17	Sales
Patel	40721	17	Other-s...
Long	40725	17	Sales
Cartes	40746	17	?
Long	40768	17	Other-s...
Cruz	40789	17	?
Moore	40727	17	Handle...
Roy	40707	17	Other-s...
Roy	40786	17	Handle...
Long	40731	17	Sales
Wong	40776	17	Adm-cl...
Jones	40758	17	Other-s...

Fig 5. Homogeneity Attack Detection Applet Page

Alice and Bob are antagonistic neighbours. One day Bob falls ill and is taken by ambulance to the hospital. Having seen the ambulance, Alice sets out to discover what disease Bob is suffering from. Alice discovers the 4-anonymous table of current inpatient records published by the hospital (Figure 2), and so she knows that one of the records in this table contains Bob's data. Since Alice is Bob's neighbor, she knows that Bob is a 31-year-old American male who lives in the zip code 13053. Therefore, Alice knows that Bob's record number is

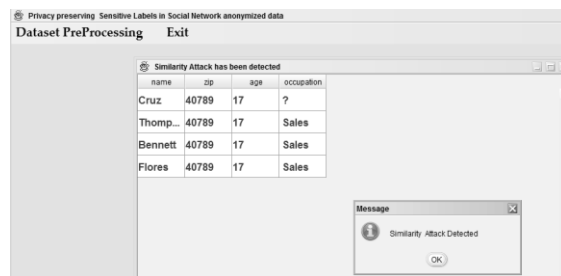
9,10,11, or 12. Now, all of those patients have the same medical condition (cancer), and so Alice concludes that Bob has cancer. The fact of Homogeneity attack is illustrated in Fig 6.8



name	zip	age	occupation
Morgan	40789	24	Machin...
Patel	40789	24	Sales
Wilson	40789	24	Adm-cl...
Mitchell	40789	24	Other-s...
Moore	40789	24	Other-s...

Fig 6. Background Knowledge Attack Detection Applet Page

Alice has a pen- friend named Umeko who is admitted to the same hospital as Bob, and whose patient records also appear in the table shown in Figure 2. Alice knows that Umeko is a 21 year- old Japanese female who currently lives in zip code 13068. Based on this information, Alice learns that Umeko's information is contained in record number 1,2,3, or 4. Without additional information, Alice is not sure whether Umeko caught a virus or has heart disease. However, it is well- known that Japanese have an extremely low incidence of heart disease. Therefore Alice concludes with near certainty that Umeko has a viral infection. The fact of Background knowledge attack is illustrated in Fig 6.9



name	zip	age	occupation
Cruz	40789	17	?
Thomp...	40789	17	Sales
Bennett	40789	17	Sales
Flores	40789	17	Sales

Fig 7. Similarity Attack Detection Applet Page

Salary and Disease are sensitive attributes. If Alice knows Bob has a low salary (20k-40k) then Alice know that he has a stomach related disease. This is because 1 -diversity takes into account the diversity of sensitive values in the group, but does not take into account the semantical closeness of the values. The fact of Similarity attack is illustrated in Fig 6.10.

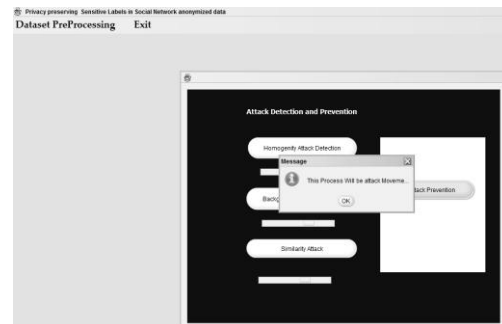


Fig 8. Attack Prevention Applet Page

The input to attack prevention module is Querying Particular Sensitive Data's in K- anonymous table and the

output is successful attack prevention and process termination. The process is carried out by checking the query for the desired character and if the attack is detected necessary steps are carried out to prevent the same as illustrated in Fig 8.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we have moved a step towards attack detection in graphical data. Several algorithms pertaining to ensuring database privacy have been studied along with the computation overhead involved in implementing the algorithms for real and synthetic data sets. Techniques for detecting abnormal graph structures such as label modifications, vertex/edge insertions and vertex/edge deletions are dealt in detail. Various types of attacks possible on social network such as active attack based on randomness, random link attack, passive attack, seed node de-identification, multiple structural attack are surveyed in detail. This paper addressed the problem of detecting three types attacks namely, homogeneity attack, background knowledge attack and similarity attack in a k-degree-1-diversity (KDLD) graph based data. In future we planned to develop novel efficient algorithms to defend against homogeneity attack, background knowledge attack and similarity attack.

REFERENCES

- [1] L. Backstrom, C. Dwork, and J.M. Kleinberg, "Wherefore Art Thou r3579x?: Anonymized Social Networks, Hidden Patterns, and Structural Steganography," Proc. Int'l Conf. World Wide Web (WWW), pp. 181-190, 2007.
- [2] A.-L. Barabási and R. Albert, "Emergence of Scaling in Random Networks," Science, vol. 286, pp. 509-512, 1999.
- [3] S. Bhagat, G. Cormode, B. Krishnamurthy, and D. Srivastava, "Class-Based Graph Anonymization for Social Network Data," Proc. VLDB Endowment, vol. 2, pp. 766-777, 2009.
- [4] A. Campan and T.M. Truta, "A Clustering Approach for Data and Structural Anonymity in Social Networks," Proc. Second ACM SIGKDD Int'l Workshop Privacy, Security, and Trust in KDD (PinKDD '08), 2008.
- [5] A. Campan, T.M. Truta, and N. Cooper, "P-Sensitive K-Anonymity with Generalization Constraints," Trans. Data Privacy, vol. 2, pp. 65-89, 2010.
- [6] J. Cheng, A.W.-c. Fu, and J. Liu, "K-Isomorphism: Privacy Preserving Network Publication against Structural Attacks," Proc. Int'l Conf. Management of Data, pp. 459-470, 2010.
- [7] G. Cormode, D. Srivastava, T. Yu, and Q. Zhang, "Anonymizing Bipartite Graph Data Using Safe Groupings," Proc. VLDB Endowment, vol. 1, pp. 833-844, 2008.
- [8] S. Das, O. Egecioglu, and A.E. Abbadi, "Privacy Preserving in Weighted Social Network," Proc. Int'l Conf. Data Eng. (ICDE '10), pp. 904-907, 2010.
- [9] W. Eberle and L. Holder, "Discovering Structural Anomalies in Graph-Based Data," Proc. IEEE Seventh Int'l Conf. Data Mining Workshops (ICDM '07), pp. 393-398, 2007.
- [10] K.B. Frikken and P. Golle, "Private Social Network Analysis: How to Assemble Pieces of a Graph Privately," Proc. Fifth ACM Workshop Privacy in Electronic Soc. (WPES '06), pp. 89-98, 2006.
- [11] S.R. Ganta, S. Kasiviswanathan, and A. Smith, "Composition Attacks and Auxiliary Information in Data Privacy," Proc. ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining, pp. 265-273, 2008.
- [12] G. Ghinita, P. Karras, P. Kalnis, and N. Mamoulis, "Fast Data Anonymization with Low Information Loss," Proc. 33rd Int'l Conf. Very Large Data Bases (VLDB '07), pp. 758-769, 2007.
- [13] G. Ghinita, P. Karras, P. Kalnis, and N. Mamoulis, "A Framework for Efficient Data Anonymization Under Privacy and Accuracy Constraints," ACM Trans. Database Systems, vol. 34, pp. 9:1-9:47, July 2009.
- [14] J. Han, Data Mining: Concepts and Techniques. Morgan Kaufmann Publishers, Inc., 2005.
- [15] M. Hay, G. Miklau, D. Jensen, D. Towsley, and P. Weis, "Resisting Structural Re-Identification in Anonymized Social Networks," Proc. VLDB Endowment, vol. 1, pp. 102-114, 2008.
- [16] E.M. Knorr, R.T. Ng, and V. Tucakov, "Distance-Based Outliers: Algorithms and Applications," The VLDB J., vol. 8, pp. 237-253, Feb. 2000.
- [17] N. Li and T. Li, "T-Closeness: Privacy Beyond K-Anonymity and L-Diversity," Proc. IEEE 23rd Int'l Conf. Data Eng. (ICDE '07), pp. 106-115, 2007.
- [18] K. Liu and E. Terzi, "Towards Identity Anonymization on Graphs," SIGMOD '08: Proc. ACM SIGMOD Int'l Conf. Management of Data, pp. 93-106, 2008.
- [19] L. Liu, J. Wang, J. Liu, and J. Zhang, "Privacy Preserving in Social Networks against Sensitive Edge Disclosure," Technical Report CMIDA-HiPSCCS 006-08, 2008.
- [20] A. Machanavajjhala, D. Kifer, J. Gehrke, and M. Venkitasubramaniam, "L-Diversity: Privacy Beyond K-Anonymity," ACM Trans. Knowledge Discovery Data, vol. 1, article 3, Mar. 2007.
- [21] A. Narayanan and V. Shmatikov, "De-Anonymizing Social Networks," Proc. IEEE 30th Symp. Security and Privacy, pp. 173-187, 2009.
- [22] C.C. Noble and D.J. Cook, "Graph-Based Anomaly Detection," Proc. Ninth ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining (KDD '03), pp. 631-636, 2003.
- [23] L. Page, S. Brin, R. Motwani, and T. Winograd, "The Pagerank Citation Ranking: Bringing Order to the Web," Proc. World Wide Web Conf. Series, 1998.
- [24] K.P. Puttaswamy, A. Sala, and B.Y. Zhao, "Starclique: Guaranteeing User Privacy in Social Networks Against Intersection Attacks," Proc. Fifth Int'l Conf. Emerging Networking Experiments and Technologies (CoNEXT '09), pp. 157-168, 2009.
- [25] N. Shrivastava, A. Majumder, and R. Rastogi, "Mining (Social) Network Graphs to Detect Random Link Attacks," Proc. IEEE 24th Int'l Conf. Data Eng. (ICDE '08), pp. 486-495, 2008.
- [26] L. Sweeney, "K-Anonymity: A Model for Protecting Privacy," Int'l J. Uncertain. Fuzziness Knowledge-Based Systems, vol. 10, pp. 557-570, 2002.
- [27] X. Xiao and Y. Tao, "Anatomy: Simple and Effective Privacy Preservation," Proc. 32nd Int'l Conf. Very Large Databases (VLDB '06), pp. 139-150, 2006.
- [28] X. Ying, X. Wu, and D. Barbara, "Spectrum Based Fraud Detection in Social Networks," Proc. IEEE 27th Int'l Conf. Very Large Databases (VLDB '11), 2011.
- [29] X. Ying and X. Wu, "Randomizing Social Networks: A Spectrum Preserving Approach," Proc. Eighth SIAM Conf. Data Mining (SDM '08), 2008.
- [30] E. Zheleva and L. Getoor, "Preserving the Privacy of Sensitive Relationships in Graph Data," Proc. First SIGKDD Int'l Workshop Privacy, Security, and Trust in KDD (PinKDD '07), pp. 153-171, 2007.
- [31] E. Zheleva and L. Getoor, "To Join or Not to Join: The Illusion of Privacy in Social Networks with Mixed Public and Private User Profiles," Proc. 18th Int'l Conf. World Wide Web (WWW '09), pp. 531-540, 2009.
- [32] B. Zhou and J. Pei, "Preserving Privacy in Social Networks Against Neighborhood Attacks," Proc. IEEE 24th Int'l Conf. Data Eng. (ICDE '08), pp. 506-515, 2008.
- [33] B. Zhou and J. Pei, "The K-Anonymity and L-Diversity Approaches for Privacy Preservation in Social Networks against Neighborhood Attacks," Knowledge and Information Systems, vol. 28, pp. 47-77, 2011.
- [34] L. Zou, L. Chen, and M.T. O'zsu, "K-Automorphism: A General Framework for Privacy Preserving Network Publication," Proc. VLDB Endowment, vol. 2, pp. 946-957, 2009.
- [35] Mingxuan Yuan, Lei Chen, Philip S. Yu, Ting Yu, "Protecting Sensitive Labels in Social Network Data Anonymization", IEEE Transactions on Knowledge and Data Engineering, Vol. 25, No. 3, March 2013
- [36] S. Balamurugan, P. Visalakshi, "Modified Partitioning Algorithm for Privacy Preservation in Microdata Publishing with Full Functional Dependencies", Australian Journal of Basic and Applied Sciences, 7(8): 316-323, July 2013

- [38] S.Charanyaa, T.Shanmugapriya, "Certain Investigations on Approaches for Protecting Graph Privacy in Data Anonymization", International Journal of Innovative Research in Computer and Communication Engineering, Vol. 1, Issue 8, October 2013
- [39] S.Charanyaa, T.Shanmugapriya, "A Survey on Attack Prevention and Handling Strategies in Graph Based Data Anonymization" International Journal of Advanced Research in Computer and Communication Engineering, Vol. 2, Issue 10, October 2013

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