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Anonymization of Centralized and Distributed Social Networks by Sequential Clustering

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Abstract:

Knowledge engineers interpret and organize information on how to make systems decisions. The social media has grown very vastly in the earlier years known think for all. There are different social media sites like Face book, Twitter, LinkedIn, Google+ and many more that holds public and confidential/ personal information about their users.we work the problem of privacy-preservation in social networks.

We consider the distributed setting in which the network data is split between several data holders. The goal is to arrive at an anonymized view of the unified network without revealing to any of the data holders information about links between nodes that are controlled by other data holders. To that end, we start with the centralized setting and offer two variants of an anonymization algorithm which is based on sequential clustering.

Our algorithms significantly outperform the SaNGreeA algorithm due to Campan and Truta which is the leading algorithm for achieving anonymity in networks by means of clustering. We then devise secure distributed versions of our algorithms. To the best of our knowledge, this is the first study of privacy preservation in distributed social networks. We conclude by outlining future research proposals in that direction.

Index Terms:

social networks; clustering; privacy preserving data mining; distributed computation; Sequential Clustering.

INTRODUCTION:

Knowledge engineers interpret and organize information on how to make systems decisions. KDEG investigates the fundamental challenges and practical applications of knowledge-driven systems. Its research combines knowledge discovery, representation and reasoning with web-based data management and intelligent systems engineering. This research is advanced through application in a number of areas. However, there were significant issues with trying to apply these conventional methods to the development of expert systems. Many of the design modeling techniques (e.g. flow charts, dataflow diagrams) that were essential to these methods were of minimal value to designing expert systems.

For example, an inference engine (the tool used by expert systems to represent and utilize expert knowledge coded as rules) attempts to abstract away from things like explicit flow of control. The control flow for an expert system can be very hard to predict because for each example the system will be driven by the particular rules that have fired.

This can be a very powerful mechanism, allowing engineers to define knowledge via rules that are independent of specific programs. However, trying to specify such rules and their control flow via diagrams that must specify predefined flow of control will be very difficult.

Indeed one of the goals of expert systems was to abstract away from specific programming. It was often claimed that expert system shells allowed the experts to become programmers and to do away with professional programmers. This was seldom true in reality but it reflects the core idea that expert system shells tried to move the definition of the system to a higher level of abstraction than conventional code.

Thus, the whole need for detailed design before programming was mostly ameliorated. Note that while design diagrams could often be minimized for the expert system itself as expert

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systems began to take off the requirement for them to integrate with existing systems and legacy databases was significant and design of such integration was a critical part of the complete knowledge engineering process. Another issue with using conventional methods to develop expert systems was that due to the unprecedented nature of expert systems they were one of the first applications to adopt rapid application development methods that feature iteration and prototyping as well as or instead of detailed analysis and design.

In the 1980's few conventional software methods supported this type of approach. Networks are structures that describe a set of entities and the relations between them. A na¨ıve anonymization of the network, in the sense of removing identifying attributes like names or social security numbers from the data, is insufficient. As shown in [2], the mere structure of the released graph may reveal the identity of the individuals behind some of the nodes. The idea behind the attack described in [2] is to inject a group of nodes with a distinctive pattern of edges among them into the network.

The adversary then may link this distinctive structure to some set of targeted individuals. When the na¨ıvely anonymized network is published, the adversary traces his injected subgraph in the graph; if successful (namely, there is only one such subgraph in the graph, an event of probability that can be made sufficiently high), the targets who are connected to this subgraph are re-identified and the edges between them are disclosed. Even less sophisticated adversaries may use prior knowledge of some property of their target nodes (say, the number of their neighbors and their interrelations) in order to identify them in the published graph and then extract additional information on them.

EXISTING SYSTEM:

A social network, for example, provides information on individuals in some population and the links between them, which may describe relations of friendship, collaboration, correspondence, and so forth. An information network, as another example, may describe scientific publications and their citation links. In their most basic form, networks are modeled by a graph, where the nodes of the graph correspond to the entities, while edges denote relations between them.

Real social networks may be more complex or contain additional information. For example, in networks where the described interaction is asymmetric (e.g., a financial transaction network), the graph would be directed; if the interaction involves more than two parties (e.g., a social network that describes co-membership in social clubs) then the network would be modeled as a hypergraph; in case where there are several types of interaction, the edges would be labeled; or the nodes in the graph could be accompanied by attributes that provide demographic information such as age, gender, location, or occupation which could enrich and shed light on the structure of the network. Such social networks are of interest to researchers from many disciplines, be it sociology, psychology, market research, or epidemiology. However, the data in such social networks cannot be released as is, since it might contain sensitive information. Therefore, it is needed to anonymize the data prior to its publication in order to address the need to respect the privacy of the individuals whose sensitive information is included in the data. Data anonymization typically trades off with utility.

DISADVANTAGES OF EXISTING SYATEM:

In an existing system, the complexity in communication increases and security level is low in social network system.Real social networks may be more complex or contain additional information.

PROPOSED SYSTEM:

In this study, we deal with social networks where the nodes could be accompanied by descriptive data, and propose two novel anonymization methods of the third category (namely, by clustering the nodes). Our algorithms issue anonymized views of the graph with significantly smaller information losses than anonymizations issued by the existing algorithms.

The study of anonymizing social networks has concentrated so far on centralized networks, i.e., networks that are held by one data holder. However, in some settings, the network data is split between several data holders, or players. For example, the data in a network of email accounts where two nodes are connected if the number of email messages that they exchanged was greater than some given threshold, might be split between several email service providers.

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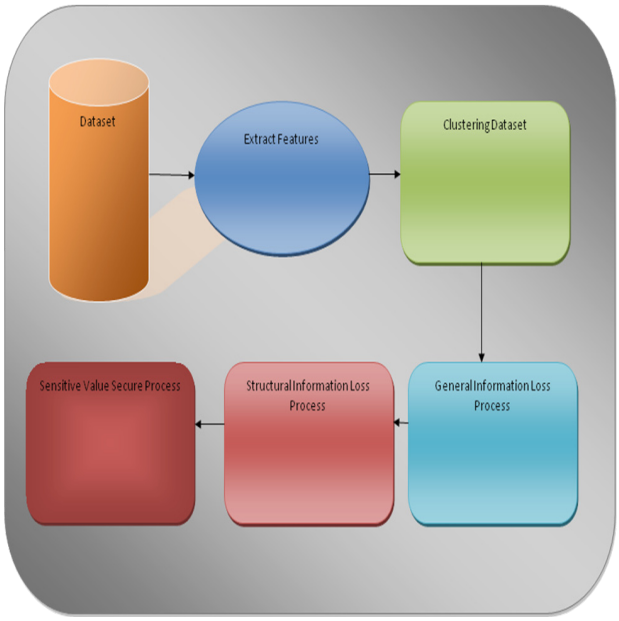
As another example, consider a transaction network where an edge denotes a financial transaction between two individuals; such a network would be split between several banks. In such settings, each player controls some of the nodes (his clients) and he knows only the edges that are adjacent to the nodes under his control. It is needed to devise secure distributed protocols that would allow the players to arrive at an anonymized version of the unified network.

Namely, protocols that would not disclose to any of the interacting players more information than that which is implied by its own input (being the structure of edges adjacent to the nodes under the control of that player) and the final output (the anonymized view of the entire unified network). The recent survey by Wu et al. about privacy-preservation in graphs and social networks concludes by recommendations for future research in this emerging area. One of the proposed directions is distributed privacy-preserving social network analysis, which "has not been well reported in literature."

ADVANTAGES OF PROPOSED SYSTEM:

We deal with social networks where the nodes could be accompanied by descriptive data, and propose two novel anonymization methods of the third category (namely, by clustering the nodes).

SYSTEM ARCHITECTURE:



MODULES DESCRIPTION:

(1)Input Dataset:

In this module, the user input the dataset for Centralized and Distributed Networks. The Dataset concept allows you to define sets of data from different tables and export this data in one step.

Datasets are especially useful for managing reference data for a module, for example tax rates or default data in new tables added by a module.

The reference data is packaged, distributed and installed together with the program code implementing the module. The content of a Dataset is defined by its Dataset Tables and Dataset Columns.

(2) Extraction:

Datasets can be defined at System, Organization, or Client/Organization levels. System-level datasets are applied when the module containing them is installed in the system.

The user extracts the particular reference value to get particular information from the input dataset. And the Extraction Pattern makes the user to refer easily whenever or whatever they are in need of it Extraction module performs action with the feature classification.

(3) Sequential Clustering :

Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters).In this dataset Sequential Clustering is done. Sequential Clustering is a topic of data mining concerned with finding statistically relevant patterns between data examples where the values are delivered in a sequence.

It is usually presumed that the values are discrete, and thus time series mining is closely related, but usually considered a different activity. Sequential pattern mining is a special case of structured data mining.

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(4) Anonymization algorithm:

Random samples were drawn from data set at nine different sampling fractions .Any identifying variables were removed and each sample was k-anonymized. An existing global optimization algorithm was implemented to k-anonymize the samples. This algorithm uses a cost function to guide the k-anonymization process (the objective is to minimize this cost). A commonly used cost function to achieve baseline k-anonymity is the discern ability metric. Finally Graph Evaluation is also made to show the performance analysis.

This Project, focus on privacy-preservation in social networks. The goal is to arrive at an anonymized view of the unified network without revealing to any of the data holders information about links between nodes that are controlled by other data holders. To that end, we start with the centralized setting and offer two variants of an anonymization algorithm which is based on sequential clustering.

Our algorithms significantly outperform the SaNGreeA algorithm due to Campan and Truta which is the leading algorithm for achieving anonymity in networks by means of clustering. We then devise secure distributed versions of our algorithms. To the best of our knowledge, this is the first study of privacy preservation in distributed social networks. Scope:-

The main scope is to arrive at an anonym zed view of the unified network without revealing to any of the data holders information about links between nodes that are controlled by other data holders. The study of anonym zing social networks has concentrated so far on centralized networks, i.e., networks that are held by one data holder. However, in some settings, the network data is split between several data holders, or players. For example, the data in a network of email accounts where two nodes are connected if the number of email messages that they exchanged was greater than some given threshold, might be split between several email service providers. As another example, consider a transaction network where an edge denotes a financial transaction between two individuals; such a network would be split between several banks. In such settings, each player controls some of the nodes (his clients) and he knows only the edges that are adjacent to the nodes under his control.

Based on these observations we focus on improving the performance of information collection from the neighborhood of a user in a social network and make the following contributions:We introduce sampling-based algorithms that given a user in a social network quickly obtain a near-uniform random sample of nodes in its neighborhood. We employ these algorithms to quickly approximate the number of users in a user's neighborhood that have endorsed an item.

We introduce and analyze variants of these basic sampling schemes in which we aim to minimize the total number of nodes in the network visited by exploring correlations across samples. We evaluate our sampling-based algorithms in terms of accuracy and efficiency using real and synthetic data and demonstrate the utility of our approach. We show that our basic sampling schemes can be utilized for a variety of strategies aiming to rank items in a network, assuming that information for each user in the network is available.

ANONYMIZATION BY SEQUENTIAL CLUSTERING :

The sequential clustering algorithm for k-anonymizing tables was presented in [7]. It was shown there to be a very efficient algorithm in terms of runtime as well as in terms of the utility of the output anonymization. We proceed to describe an adaptation of it for anonymizing social networks. Algorithm 1 starts with a random partitioning of the network nodes into clusters.

The initial number of clusters in the random partition is set to N/koand the initial clusters are chosen so that all of them are of size ko or ko + 1, where ko = αk is an integer and α is some parameter that needs to be determined. The algorithm then starts its main loop (Steps 2-4). In that loop, the algorithm goes over the N nodes in a cyclic manner and for each node it checks whether that node may be moved from its current cluster to another one while decreasing the information loss of the induced anonymization.

Algorithm:

Algorithm 1.

- Input: A social network SN, an integer k.
- Output: A clustering of SN into clusters of size ≥ k.

1) Choose a random partition C = {C1,...,CT} of V into T := N/ko clusters of sizes either koor ko+ 1.

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2) For n = 1,...,N do:
a) Let Ctbe the cluster to which vn currently belongs.
b) For each of the other clusters, Cs, s = t, compute the difference in the information loss, Δn:ts, if vn would move from Ctto Cs.
c) Let Csobe the cluster for which Δn:tsis minimal.
d) If Ct is a singleton, move vn from Ct to Cso and remove cluster Ct.
e) Else, if Δn:tso< 0, move vnfrom Ctto Cso.
3) If there exist clusters of size greater than k1, split each of them randomly into two equally-sized clusters.
4) If at least one node was moved during the last loop, go to Step 2.
5) While there exist clusters of size smaller than k, select one of them and unify it with the cluster which is closest.
6) Output the resulting clustering.

Explanation:

Computing the sum of private integers has well known simple SMPs. The components of the vectors are rational numbers The denominators of those numbers are common and known to all, but their numerators depend on private integers (those are the private integers that appear in the numerator Hence, that problem reduces to computing sums of private vectors over the integers. Moreover, it is possible to compute upfront an upper bound p on the size of those integers and of their sum.

Algorithm 2. Secure computation of sums:

• Input: Each player m, 1 ≤ m ≤ M, has a private input vector am Zd p.
• Output: a =∑M m=1am.
1) Player m selects M random share vectors am,ℓ Zd p, 1 ≤ ℓ ≤ M, such that∑M ℓ=1am,ℓ= ammod p.
2) Player m sends am,ℓto the ℓth player, for all 1 ≤ ℓ = m ≤ M.
3) Player ℓ, 1 ≤ ℓ ≤ M, computes sℓ=∑M m=1am,ℓmod p.
4) Players ℓ, 2 ≤ ℓ ≤ M, send sℓto the player 1.
5) Player 1 computes a =∑M ℓ=1sℓmod p and broadcasts it.

THE DISTRIBUTED SETTING:

Here we consider the distributed setting, in which the network data is split among M sites (or players) in the following manner: player m, 1 ≤ m ≤ M, holds Nm of the nodes, say V m = {vm 1 , . . . , vm Nm } Σ
. The overall number of nodes is N = M m=1 Nm and the unified set of nodes is V = M m=1 V m. As for the structural data, E (V 2) , it is split between the players in the following manner: Edges that connect two nodes in V m are known only to player m; edges that connect nodes in V m and V m are known only to players m and m. There are two scenarios to consider in this setting:

1) Scenario A: Each player needs to protect the identities of the nodes under his control from other players, as well as the existence or non-existence of edges adjacent to his nodes.

2) Scenario B: All players know the identities of all nodes in V ; the information that each player needs to protect from other players is the existence or non-existence of edges adjacent to his nodes.

To illustrate the difference between the two scenarios, let us return to the toy network in the left of Figure 1. Assume that it is split between three players — the "circular", the "square", and the "triangular" players; namely, the circular player controls the three circular nodes in the graph, while the square and triangular players control the corresponding square and triangular nodes.

Assume that those players are banks, that the nodes are accounts in those banks, and that the edges denote financial transactions between the accounts. Here, each node is identified by an account number, but the bank is trusted to protect the identity of the clients that hold those accounts. Hence, the square bank is expected to hide the information that one of his clients is a 62 year old female and the other is a 31 year old female (as indicated by the quasi identifier records (62,F) and (31,F) next to his nodes in Figure 1) since that might reveal the identity of the account holders.In addition, the square bank is expected to hide from the circular bank the internal transactions among his clients (there is one such edge in the illustrated graph) or between his clients and clients of the triangular bank (there are two such edges in the graph). This is an example of Scenario A. However, assume that the network is a correspondence network between email addresses. Here it is natural to assume that the identity of the nodes is not confidential, since typical email addresses disclose the name of the individual that holds them.

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Privacy:

A perfectly secure multiparty protocol does not reveal to any of the participating parties more information than what is implied by their own input and the final output. While such perfect security may be theoretically achieved, as was shown by Yao in [25], some relaxations are usually inevitable when looking for practical solutions, provided that the excess information is deemed benign (see examples of such protocols in e.g. [13], [21], [30]). Our protocol is not perfectly secure. In Theorem we bound the excess information that it may lead to the interacting players. We then proceed to argue why such leakage of information is benign.

Communication complexity:

Let L denote the number of iterations in the sequential algorithm. During the main loop, we need to compute for each node the differences in the structural information loss if that node moves to any of the other clusters. As explained in Section, this may be done by one invocation of an SMP to compute a sum of private vectors (Algorithm 2).

Hence, the number of SMP calls in the main loop is NL. In the agglomerative stage that follows, there is a need in one invocation of the SMP for each small cluster. Since Step 5 may be repeated at most N times (and typically much less) the overall number of SMP calls in the entire protocol is bounded by N(L + 1). Finally, as Algorithm 2 entails 3 communication rounds, the overall round complexity of the protocol is bounded by 3N(L + 1).

CONCLUSION:

We presented sequential clustering algorithms for anonymizing social networks. Those algorithms produce anonymizations by means of clustering with better utility than those achieved by existing algorithms. We devised a secure distributed version of our algorithms for the case in which the network data is split between several players.

We focused on the scenario in which the interacting players know the identity of all nodes in the network, but need to protect the structural information (edges) of the network (Scenario B, as defined in Section 5).

One research direction that this study suggests is to devise distributed algorithms also to Scenario A. In that scenario, each of the players needs to protect the identity of the nodes under his control from the other players.

Hence, it is more difficult than Scenario B in two manners: It requires a secure computation of the descriptive information loss (while in Scenario B such a computation can be made in a public manner); and the players must hide from other players the allocation of their nodes to clusters. Another research direction that this study suggests is to devise distributed versions of the k-anonymity algorithms in [15], [23], [31]; those algorithms might require different techniques than those used here.

REFERENCES:

[1] G. Aggarwal, T. Feder, K. Kenthapadi, R. Motwani, R. Panigrahy, D. Thomas, and A. Zhu. Anonymizing tables. In ICDT, volume 3363 of LNCS, pages 246–258, 2005.

[2] L. Backstrom, C. Dwork, and J. M. Kleinberg. Wherefore art thou r3579x?: anonymized social networks, hidden patterns, and structural steganography. In WWW, pages 181–190, 2007.

[3] A. Barab´asi and R. Albert. Emergence of scaling in random networks. Science, 286:509–512, 1999.

[4] J. Benaloh. Secret sharing homomorphisms: Keeping shares of a secret secret. In Crypto, pages 251–260, 1986.

[5] F. Bonchi, A. Gionis, and T. Tassa. Identity obfuscation in graphs through the information theoretic lens. In ICDE, pages 924–935, 2011.

[6] A. Campan and T. M. Truta. Data and structural k-anonymity in social networks. In PinKDD, pages 33–54, 2008.

[7] J. Goldberger and T. Tassa. Efficient anonymizations with enhanced utility. TDP, 3:149–175, 2010.

[8] S. Hanhij¨arvi, G. Garriga, and K. Puolamaki. Randomization techniques for graphs. In SDM, pages 780–791, 2009.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

[9] M. Hay, G. Miklau, D. Jensen, D. F. Towsley, and P. Weis. Resisting structural re-identification in anonymized social networks. In PVLDB, pages 102–114, 2008.
[10] M. Hay, G. Miklau, D. Jensen, P. Weis, and S. Srivastava. Anonymizing social networks. Uni. of Massachusetts Technical Report, 07(19), 2007.

[11] V. Iyengar. Transforming data to satisfy privacy constraints. In ACMSIGKDD, pages 279–288, 2002.

[12] W. Jiang and C. Clifton. A secure distributed framework for achieving k-anonymity. The VLDB Journal, 15:316–333, 2006.

[13] M. Kantarcioglu and C. Clifton. Privacy-preserving distributed mining of association rules on horizontally partitioned data. IEEE Trans. Knowl. Data Eng., 16:1026–1037, 2004.

[14] S. Kirkpatrick, D. G. Jr., and M. P. Vecchi. Optimization by simulated annealing. Science, 220(4598):671–680, 1983.

[15] K. Liu and E. Terzi. Towards identity anonymization on graphs. In SIGMOD Conference, pages 93–106, 2008.

[16] A. Machanavajjhala, D. Kifer, J. Gehrke, and M. Venkitasubramaniam. ℓ-diversity: Privacy beyond k-anonymity. ACM Trans. Knowl. Discov. Data, 1(1):3, 2007.

[17] M. E. Nergiz and C. Clifton. Thoughts on k-anonymization. In ICDE Workshops, page 96, 2006.

[18] A. Schuster, R. Wolff, and B. Gilburd. Privacy-preserving association rule mining in large-scale distributed systems. In CCGRID, pages 411– 418, 2004.

[19] N. Slonim, N. Friedman, and N. Tishby. Unsupervised document classification using sequential information maximization. In SIGIR, pages 129–136, 2002.

[20] L. Sweeney. Uniqueness of simple demographics in the U.S. population. In Laboratory for International Data Privacy (LIDAP-WP4), 2000.

[21] J. Vaidya and C. Clifton. Privacy preserving association rule mining in vertically partitioned data. In KDD, pages 639–644, 2002.

[22] D. Watts and S. Strogatz. Collective dynamics of 'small-world' networks. Nature, 393:409–410, 1998.

[23] W. Wu, Y. Xiao, W. Wang, Z. He, and Z. Wang. k-Symmetry model for identity anonymization in social networks. In EDBT, pages 111–122, 2010.

[24] X. Wu, X. Ying, K. Liu, and L. Chen. A survey of privacy-preservation of graphs and social networks. In C. Aggarwal and H. Wang, editors, Managing and mining graph data, chapter 14. Springer-Verlag, first edition, 2010.

[25] A. Yao. Protocols for secure computation. In Symposium on Foundations of Computer Science (FOCS), pages 160–164, 1982.

[26] X. Ying and X. Wu. Randomizing social networks: A spectrum preserving approach. In SDM, pages 739–750, 2008.

[27] X. Ying and X. Wu. Graph generation with prescribed feature constraints. In SDM, pages 966–977, 2009.

[28] X. Ying and X. Wu. On link privacy in randomizing social networks. In PAKDD, pages 28–39, 2009.

[29] E. Zheleva and L. Getoor. Preserving the privacy of sensitive relationship in graph data. In PinKDD, pages 153–171, 2007.

[30] S. Zhong, Z. Yang, and R. Wright. Privacy-enhancing k-anonymization of customer data. In PODS, pages 139–147, 2005.

[31] B. Zhou and J. Pei. Preserving privacy in social networks against neighborhood attacks. In ICDE, pages 506–515, 2008.