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Anonymous Community Identification on Published Social Networks

[1]Dr. A.N. Nanda Kumar, [2]Mr. S. Niresh Kumar, [3]Mrs. M. Behima,
[1]Dhanalakshmi Srinivasan College of Engineering and Technology
[2]Dhanalakshmi Srinivasan College of Engineering and Technology
[3]Dhanalakshmi Srinivasan College of Engineering and Technology

ABSTRACT: *The amount of date and knowledge through data shared via social media is rapidly increasing amid growing concerns over online privacy. the Objective of this paper is to investigate the effect of controversy and social endorsement of media content on sharing behavior when choosing between sharing publicly or anonymously. An untrusted site where data sharing is found to be a well-liked choice (59% of shares), especially for controversial content which is 3.2x more likely to be shard anonymously. Social endorsement wasn't found to affect sharing behavior, aside from sports-related content. Implications for social media interface design are discussed.*

INDEX TERMS—*Social network, privacy, anonymization.*

I. INTRODUCTION

As an increasing number of social networking data is published and shared for commercial and research purposes, privacy issues about the individuals in social networks have become serious concerns. Vertex identification, which identifies a particular user from a network based on background knowledge such as vertex degree, is one of the most important problems that have been addressed. In reality, however, each individual in a social network is inclined to be associated with not only a vertex identity but also a community identity, which can represent the personal privacy information sensitive to the public, such as political party affiliation.

The performance studies on real data sets from various perspectives demonstrate the practical utility of the proposed privacy scheme and our anonymization approaches.

In a social network, individuals are represented by vertices, and the social activities between individuals are summarized by edges. In light of the recognition of the usefulness of information in social networking data for commercial and research purposes, more and more social networking data have been published and shared in recent years. Individual in a social network is associated with a vertex identity, which can represent the user name or social security number (SSN) which is based on the user attributes. An attacker knows a piece of information about an individual; it is insufficient to protect privacy by only removing the vertex identities. To hide privacy details about each individual by grouping a set of vertices into a super-vertex and inferring the relationships between super-vertices from super-edges. The community identity of a vertex can represent the personal privacy information sensitive to the public, such as online political activity group, online disease support. We propose Integer Programming formulation to find optimal solutions for small instances. In addition, we also devise scalable heuristics to solve large-scale instances of k-SDA with different perspectives. To demonstrate the practical utility of the proposed privacy scheme and our anonymization approaches, various evaluations are performed on real data sets. The experimental results show that the social networks anonymized by our approaches can preserve much of the characteristics of the original networks.

II. SYSTEM ANALYSIS

EXISTING SYSTEM

First addresses the new privacy issue, referred to as community identification, by showing that the community identity of a victim can still be inferred even though the social network is protected by existing anonymity schemes.

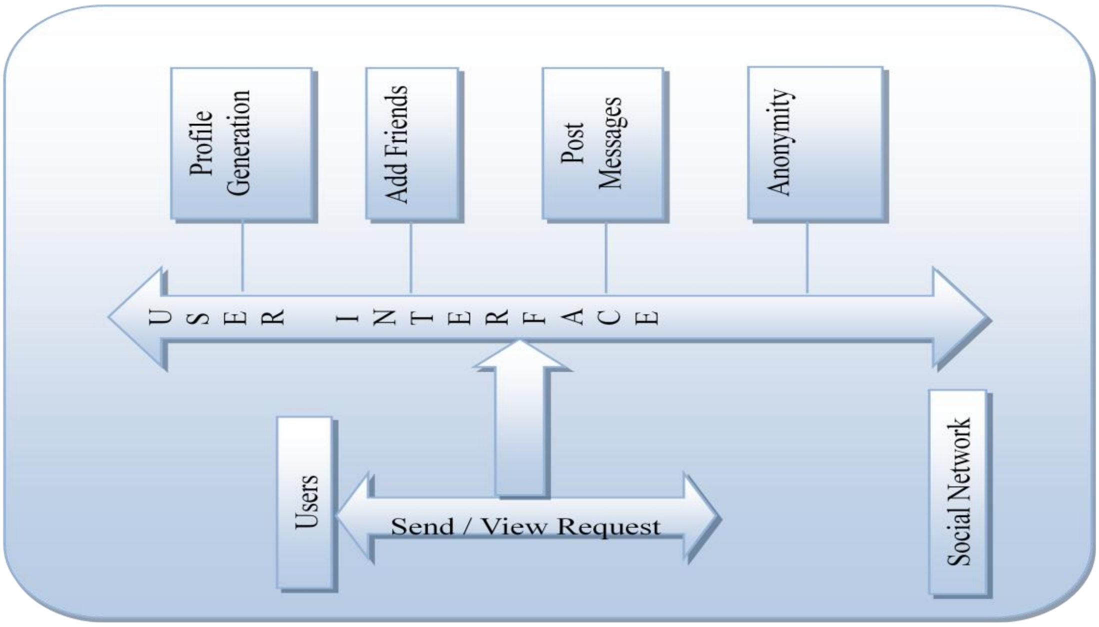
PROPOSED SYSTEM

To resolve the above issue propose the concept of structural diversity to provide the anonymity of the community identities. The k-Structural Diversity Anonymization (k-SDA) is to ensure sufficient vertices with the same vertex degree in at least k communities in a social network.

Also, Integer Programming formulation is proposed to find optimal solutions to k-SDA and also devise scalable heuristics to solve large-scale instances of k-SDA from different perspectives.

III. SYSTEM ARCHITECTURE

System architecture can comprisesystem components, the externally visible properties of those components, the relationships (e.g. the behavior) between them. It can provide a plan from which products can be procured, and systems developed, that will work together to implement the overall system. We then propose the concept of structural diversity to provide the anonymity of the community identities. The k-Structural Diversity Anonymization (k-SDA) is to ensure sufficient vertices with the same vertex degree in at least k communities in a social network. We propose an Integer Programming formulation to find optimal solutions to k-SDA and also devise scalable heuristics to solve large-scale instances of k-SDA from different perspectives. The performance studies on real data sets from various perspectives demonstrate the practical utility of the proposed privacy scheme and our anonymization approaches.

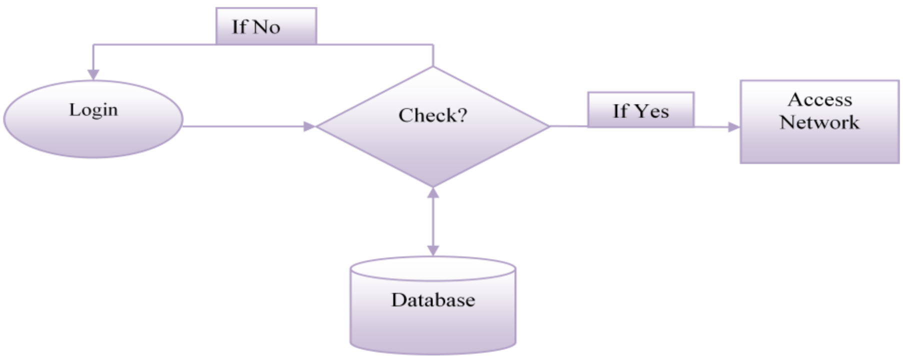


System Architecture of anonymous community identification

IV. MODULES

AUTHENTICATION

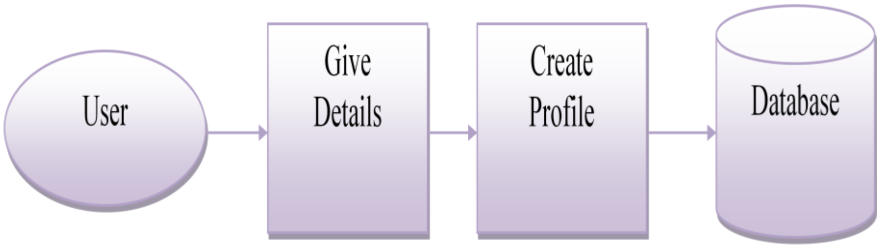
If you are the new user going to access the network then they have to register first by providing necessary details. After successful completion of sign up process, the user has to login into the application by providing username and exact password. The user has to provide exact username and password which was provided at the time of registration, if login success means it will take up to main page else it will remain in the login page itself.



Authentication

PROFILE GENERATION

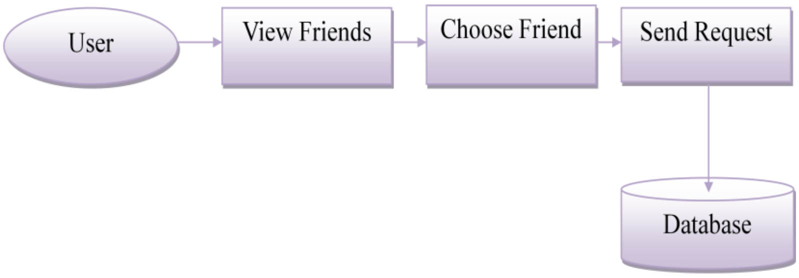
In this module, the users can enter the personal details in to the social network web and makes the profile for personal use. If you are creates profile it will be stored in database with unique id (Individual Profile).



Profile Generation

SEND REQUEST

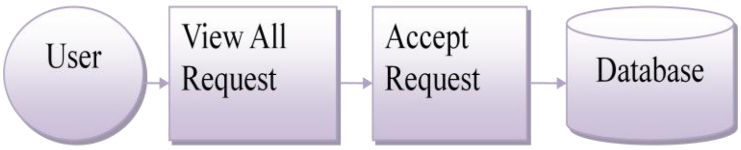
In this module user can view all the friends based on their individual identities in the social network. And also sends the request to the particular friend this information stored in database. This module is may used to create the network community.



Send Request

ACCEPT REQUEST

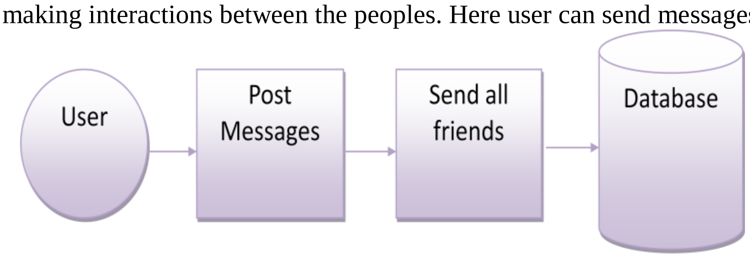
In this module we see the requests and accept for add friends to my circle and this generated information's has stored into database.



Accept Request

POST MESSAGES

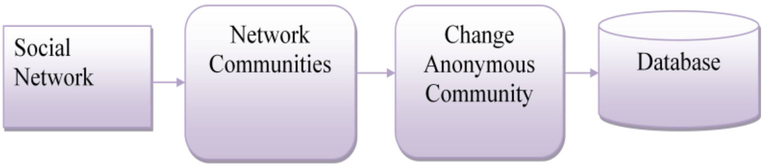
This module used to making interactions between the peoples. Here user can send messages to his entire friend.



Post Messages

ANONYMITY

This module used to make the anonymous community based on the existing communities, which are used to hide the personal or sensitive information. Here the normal communities can converted into anonymous communities.



Anonymity

K-STRUCTURAL DIVERSITY ANONYMIZATION

Edge Connect select largest degree vertex. Adding edges**,** Examines every new edge (w; v) incident to v to find VCv _ Nw, where VCv is the set of not-yet-anonymized vertices in the samecommunity of v, and Nw is the set of neighboring vertices of w. We add (w; v) to Rv if VCv _ Nw is not an empty set. Redirecting edges if the edges are redirectable It Should not in the same communities. Mergence is the way to allow v to join the group with a smaller degree. Splitting Vertex is proposed to ensure that any arbitrary input instance can be anonymized to achieve kstructural diversity. CreateBySplit Splitting Vertex will increase the number of vertices in a community and provide a greater number of chances to achieve the anonymization., MergeBySplit can anonymize every social network, even for the most difficult one, FlexSplit which identifies a group of vertices and splits these vertices to generate a new anonymous group of a target degree and it reduces the number of substitute vertices.

INTEGER PROGRAMMING

In the following, we propose the Integer Programming formulation for k -SDA. Our formulation together with any commercial software for mathematical programming canfind the optimal solutions, which can be used as the benchmarks for the solutions obtained by any heuristic algorithm. We first derive the formulation for k-SDA with only operation Adding Edge to capture the intrinsic characteristics of this optimization problem and to avoid initially including complicated details. Thereafter, weextend the formulation to incorporate both operations with Adding Edge As an initial basis, consider the formulation for k-SDA withonly operation Adding Edge. The degree for each vertex u mustbe no smaller than the number of originally incident edges. In addition, it cannot exceed the sum of the number of originally incident edges and the number of adding edge candidates. The left-hand side of constraint (3) representsthe degree of vertex u, and constraint (1) guarantees that is 1 for only a single d. In this way, constraint (3) together with constraint (1) ensure that binary variable can find the correct degree of each vertex.

V. ALGORITHM EDGECONNECT

The EdgeConnect algorithm is designed for minimizing information distortion on large-scale graphs. For this purpose, the Edge Connect algorithm incorporates operation Adding Edge to anonymize the vertices one-by-one in decreasing order of their degrees to avoid enumerating all possible combinations, which is computationally infeasible. One merit of Edge Connect is that the existing information is never removed, and the added local new edges within each community incur few changes to the whole graph. Moreover, procedures CREATION and MERGENCE are utilized in this algorithm, and any existing k-SDA group is never removed to avoid reanonymizing the vertices and increasing the computation cost. As a result, Edge Connect has very good scalability, which is shown in our experiments. The rationale of Algorithm EdgeConnect is to adjust the vertex degrees one-by-one with operation Adding Edge to let every vertex share the same degree with other vertices in at least k different communities. To avoid examining all possibilities, the anonymization begins from a not-yet anonymized vertex v of the largest degree, since the power law degree distribution demonstrated in the previous social network analysis indicates that each large degree has fewer vertices required to be anonymized. For a chosen v, Edge Connect utilizes procedure MERGENCE and CREATION to explore the way to anonymize v with minimal number of new edges. Procedure MERGENCE aims at adjusting the degree for a vertex v to join an existing k-SDA group, while CREATION is designed to collaborate with other not-yet anonymized vertices to generate a new k-SDA group with a new degree. In the example of Fig. 5a, the first vertex to be anonymized is vertex c because its degree is the largest one .At the beginning, procedure MERGENCE is unable to anonymizec because no k-SDA group has been generated, and procedure CREATION, thus, generates a new anonymous group of degree 5 by adding an edge connecting f and another vertex in the same community, such as g. At this point, the new k-SDA group is {c, f} Edge Connect repeats the above process until all the vertices are successfully anonymized. The details of each step are presented as follows: First, procedure MERGENCE protects a vertex v with an existing k-SDA group gd. As all vertices in k-SDA group gdshare the same degree d for structural diversity, the cost for v to be anonymized (by the operation Adding Edge) in gdis

VI. CONCLUSION

In this paper, the experiment results showed that our approach Works well in domains where there are enough hyponym relations. This approach may not work well in a domain where the hyponym relations among domain-specific terms are very sparse, such as human individuals or companies.

REFERECES

[1]. U.Alon, "Network Motifs: Theory and Experimental Approaches, "Nature Reviews Genetics, vol.8,no.6,pp.450461, 2007.

[2]. C.Andrew, B. Justin, K. Bryanetal., "Toward an Architecture for Never ending Language Learning,"Proc.24thNational Conf. Artificial Intelligence (AAAI10),pp.13061313,2010.

[3]. N.Y.Asuka Sumida, and K.Torisawa, "Boosting Precision and Recall of Hyponymy Relation Acquisition from Hierarchical Layouts in Wikipedia," Proc. Intl Conf. Language Resources and Evaluation (LERC08),pp.24622469,2008.

[4]. J. Carletta, "Assessing Agreement on Classification Tasks: the Kappa Statistic," Computational Linguistics, vol. 22, no. 2, pp. 249254,1996.

[5]. S. Chernov, T. Iofciu, W. Nejdl et al., "Extracting Semantic Relationships between Wikipedia Categories," Proc. 1st Intl Workshop on FromWikitoSemantics",2006.