Towards Measuring Knowledge Exposure in Online Social Networks

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***Abstract*—We propose a novel metric to measure users' exposure to various pieces of knowledge in an Online Social Network (OSN). Knowledge exposure considers not only the availability of information to users but also the effort it takes to discover it. We calculate knowledge exposure by performing link analysis on a navigation graph that models OSN's user interface. Our experiments show that the proposed metric can discriminate among pieces of knowledge based on how they are presented to users. We expect such an exposure metric to be useful as an input to privacy control policies and to enhance user privacy management in social networking environments in general.**

***Keywords*-privacy; online social networks; exposure;**

I. Introduction

Online Social Networks (OSNs) such as Facebook and Google+ are places where users share personal and potentially privacy-sensitive information with other users online. Although sharing in these systems are primarily targeted towards "friends", users face many challenges in managing who can access those information [1]–[3]. There have been various theories and solutions for privacy settings presented in the literature such as relationship-based access control policies [4]–[8], intelligent tools for privacy management [9], [10], and analysis of privacy control policies [11], [12].

One major aspect of user privacy that has been mostly overlooked in the literature is the visibility or exposure of a piece of information in an OSN; that is how easy is for someone to discover some information. Note that such a notion of exposure is different from a grant/deny decision according to some privacy control policies. Even though a user may be authorized to view two different pieces of information she might be exposed more to one than the other. For example, consider the case of news feed on Facebook. News feed is a dynamically updated list on your Facebook home page that shows recent activities of your friends such as posting status updates, becoming friends with others, etc. Let us assume Alice, who is your friend, becomes friends with Bob. You would be more exposed to that friendship if you see it as a story on your news feed than if you have to browse Alice's profile page to discover it. In fact, users showed privacy concerns when Facebook introduced the news feed feature [13], although they already were able to discover the presented information (although with more effort).

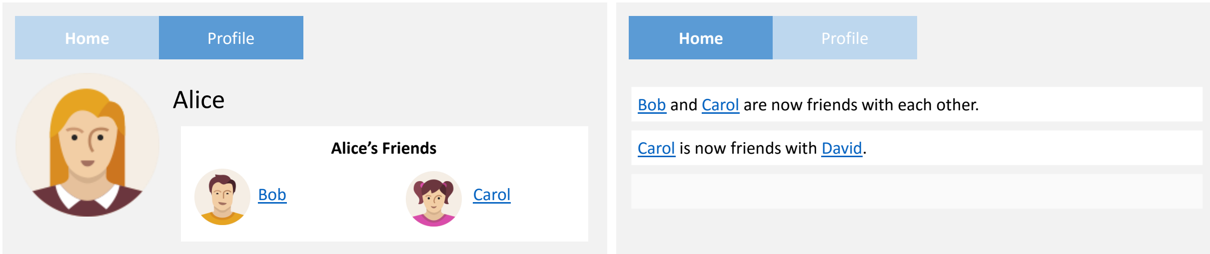
Mondal et al. [14] have recently proposed to use a variation of exposure as an alternative to access control for managing user privacy. They define exposure of a piece of information as the set of users who are expected to know about it eventually. They also outline a conceptual solution where OSNs predict popularity of items (based on various existing item popularity measures for social networks), and enable users to tune the exposure of their items. For example, they suggest allowing users to enable/disable dissemination channels or provide expressive access control policies. Although, the definition of exposure by Mondal et al. is conceptually important and novel, their proposed solution does not seem to support the exact concept in practice; popularity of information items does not quite capture the set of expected recipients of information.

We take an alternative (and more direct) approach in this work by defining the exposure of a piece of information as the extent of its discoverability by users. In other words, we are interested to measure the probability of a user being exposed to the information. We argue that the interface design of an OSN has a major impact on information exposure. Therefore, we propose a measurement approach that can consider interface design features in existing OSNs such as hyperlink-based navigation and dynamic pages. Moreover, we demonstrate through a preliminary experiment on a real-world dataset how such an exposure measurement approach is able to discriminate between various pieces of knowledge accessible by users.

The rest of the paper is organized as follows. We provide an overview of an OSN design and our solution to exposure measurement in Section II. In Section III, we present our model of knowledge and navigation in an OSN. We propose our exposure calculation approach and discuss our preliminary results in Sections IV and V, respectively. We conclude our paper with a discussion of related work (Section VI), our contributions and future work (Section VII).

II. Overview of the Proposed Approach

A user may have access to a great amount of knowledge in an OSN. But she may have different amount of exposure to different parts of the knowledge available to her. This



(a) Profile Page

(b) Home Page and News Feed

Figure 1: Pages in Our Simplified OSN

is especially true in the presence of various information presentation channels in a web-based OSN. For instance, while users can browse through various pages to discover information on Facebook, the news feed constantly pushes information to them. Intuitively, users are more exposed to the information revealed through the news feed than those that they need to discover on their own. Our goal is to introduce measures that can differentiate among those levels of exposure.

A. A Simplified OSN

We consider a simplified Facebook-like OSN where users can become friends with each other, and the main knowledge being shared is the existence of such friendships. In other words, we do not consider any mechanisms for users to share and browse contents (status updates, photos, etc.) We refer to such a simplified notion of an OSN wherever we discuss about "OSN" in the rest of this paper. We defer modeling a more realistic OSN with more complex features to our future work.

In our OSN, each user has a profile page where her full name and profile picture are displayed. Also, the profile page shows a list of the user's friends including their names and pictures, with hyperlinks to respective profile pages. Users can follow the links to browse profile pages of the user's friends. Fig. 1a shows an example profile page in our OSN. Moreover, each user has a unique home page where her news feed shows recent stories in the user's immediate friendship neighborhood. The news feed is very similar to what you might experience on Facebook. But since we limit the scope of knowledge stored by OSN, the news feed is simply a list of friendship stories, sorted in inverse chronological order. A user will see a story if any of her friends has become friends with another person. Each friendship story includes the names of the two individuals that have become friends and hyperlinks to their profile pages. Fig. 1b shows a sample home page in our OSN.

In addition, we assume that there are no privacy options for users to disallow others from accessing their profiles. Users will be able to browse any profile page as long as they can follow a hyperlink to that profile. This approach allows us to disregard the ownership of knowledge as a factor in our measurement, which intuitively adds a lot of complications. We plan to address the problem of measuring exposure in presence of privacy settings in our future work.

B. Calculating Exposure

In our web-based OSN, information is revealed to users as they browse the contents of different hyperlinked pages. For example, by browsing Bob's profile page, Alice will know Bob's name, see his profile picture, and know who his friends are. Furthermore, she can follow links to profile pages of Bob's friends in order to know more about them.

There exists a mapping between the information presented on OSN pages and the knowledge stored by the OSN. The knowledge stored by the OSN consists of users' names, profile pictures, and their friendships. Alice will be exposed to a part of such knowledge by browsing each page. In fact, the mapping between page contents and OSN knowledge happens in the application logic as the OSN retrieves parts of the knowledge and constructs a page with the (partial) knowledge. Note that the page-knowledge mapping is not necessarily one-to-one. Same information can be presented on different pages. In our approach, we model the knowledge contained in the OSN and user navigation using graphs. We explain those models including the correspondence mappings in Section III. Fig. 2 depicts our conceptual model of knowledge and pages.

Our approach to measuring exposure is to calculate an exposure score for each OSN page and transfer such score to the knowledge represented by the page. In order to calculate an exposure score for OSN pages we rely on performing link analysis on the navigation graph. Then, the exposure score for an item in the knowledge graph is an aggregation of the exposure scores of the corresponding pages. Exposure measurement will be discussed in detail in Section IV.

III. Knowledge and Navigation

A. Knowledge Graph

We represent the knowledge stored by the OSN as a graph composed of typed vertices and typed edges. Each vertex represents either a user or a data value. Each edge relates

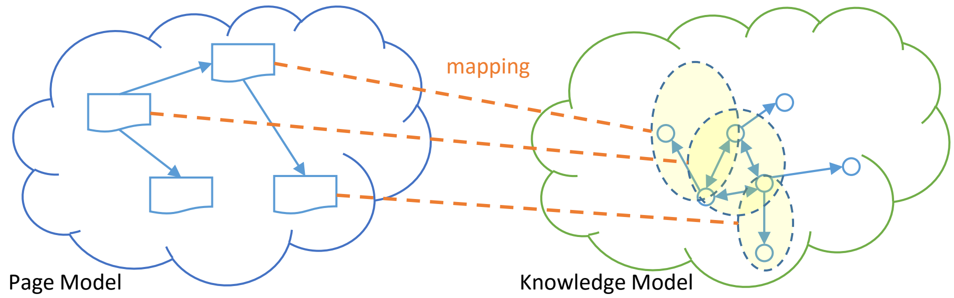


Figure 2: Knowledge, Pages, and Their Correspondence Mapping

two vertices based on some predefined types. In addition, each edge has a timestamp indicating when that edge has been created. For example, in Fig. 3, vertices `uAlice` and `uBob` represent two users. Together with their connecting `isFriendOf` edge they represent that Alice and Bob are friends. Vertex `dAliceName` represents the textual value "Alice." Vertices `uAlice`, `dAliceName`, and connecting edge `hasName` represent that Alice's name is textual value "Alice."

Definition 1 (Knowledge Graph): Knowledge Graph G_K is a pair $\langle V_K, E_K \rangle$, where V_K is a set of vertices representing abstract entities, and $E_K \subseteq V_K \times V_K$ is a set of directed edges connecting members of V_K representing relationships between them. For each vertex $v \in V_K$, $type(v) \in \{\texttt{user}, \texttt{data}\}$ denotes its type. For each edge $e \in E_K$, $type(e) \in \{\texttt{isFriendOf}, \texttt{hasName}, \texttt{hasProfilePic}\}$ denotes its type, and $time(e)$ denotes its timestamp.

We consider each edge in the knowledge graph representing a *simple knowledge statement*.

Definition 2 (Simple Knowledge Statement): A simple knowledge statement is represented by $e = \langle v, w \rangle \in E_K$, and is denoted by $type(e)(v, w)$.
For example, the statement of friendship between Alice and Bob can be shown as `isFriendOf(uAlice, uBob)`. A collection of simple knowledge statements can form a *composite knowledge statement*. In graph terms, a composite knowledge statement can be expressed as the union of corresponding edges.

B. Presenting Knowledge to Users

The functions provided by the OSN to users can be modeled as either retrieval, insertion, or deletion of knowledge statements (retrieval or manipulation of the knowledge graph). Since we are interested in measuring exposure in this work, we only discuss retrieval of such statements. When the OSN presents some information to a user it essentially retrieves a (simple/composite) statement and exposes it to the user. For instance, suppose the OSN shows to Oscar in his news feed that Alice is now friends with Bob. The system essentially exposes the following composite knowledge statement: {`isFriendOf(uAlice, uBob)`, `hasName(uAlice, dAliceName)`, `hasName(uBob, dBobName)`}

C. Navigation Graph

An OSN user is exposed to the knowledge contained in the system through the user interface. We assume that the OSN's user interface is a hyperlinked structure of pages. As the user visits a page she is exposed to the information on the page, and she can navigate to other pages using the hyperlinks on the page. We can model such a structure as a graph, where vertices and edges represent pages and hyperlinks in the user interface, respectively.

Modeling whole pages as vertices has some drawbacks for complex and dynamic pages. For instance, the news feed page in our simplified OSN (see Section II-A) presents a list of stories, which are sorted in inverse chronological order. Also, the list need to be dynamically and iteratively loaded because of its excessive length. In such a setting, we intuitively expect that at any moment the stories that appear at the top of the news feed get more exposure than those presented further down in the list. However, we cannot make that distinction using the above-mentioned graph model since a complex page is represented using one vertex, regardless of the various pieces of information it presents. Our approach is to break down complex pages into pieces, called *page atoms*. For instance, we model the news feed as a sequence of page atoms, each linking to the next page atom in the list. Each page atom may present one or multiple stories to the user. For example, we can choose the number of stories per page atom to be equal to the the number of stories that would fit on user's screen at a time. The choice affects the granularity and complexity of our algorithms. We formally define our *navigation graph* model as follows.

Definition 3 (Navigation Graph): Navigation Graph G_N is a pair $\langle V_N, E_N \rangle$, where V_N is a set of vertices representing pages or page atoms on the OSN, and $E_N \subseteq V_N \times V_N$ is a set of directed edges representing the navigation links according to the hyperlink structure of the OSN or the relationships among pages and page atoms.
Navigation graph is built according to the design and hyperlink structure of the OSN, and based on the knowledge graph

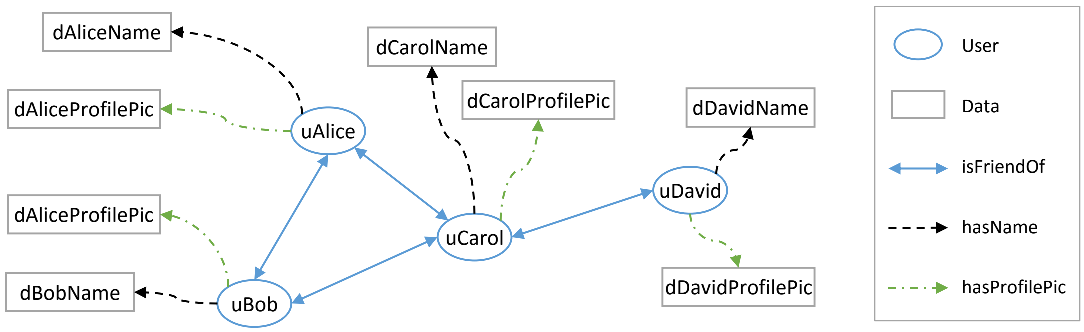


Figure 3: Sample Knowledge Graph

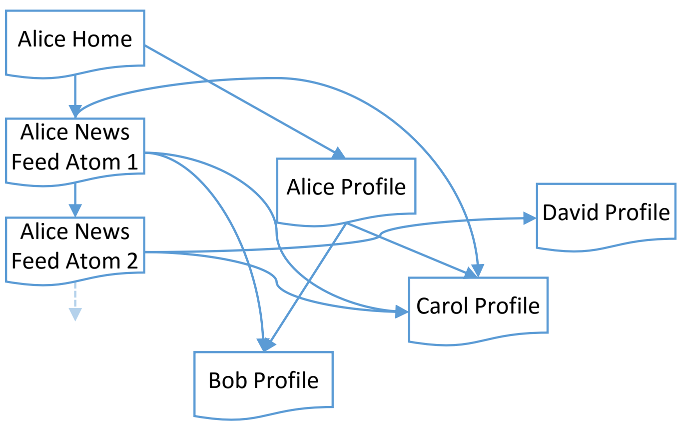


Figure 4: Partial Navigation Graph Corresponding to Pages in Fig. 1 and Knowledge Graph in Fig. 3

of the OSN at a given moment. As described in Section II-A, our OSN pages include a profile page and a home page per user. Also, a user's profile page includes hyperlinks to profile pages for the user's friends. Fig. 4 depicts a part of the navigation graph generated for the pages shown in Fig. 1 and the knowledge graph shown in Fig. 3. For brevity reasons, we only show a part of the graph concerning Alice's home page and profile page.

We capture the correspondence mapping between navigation graph and knowledge graph as follows.

Definition 4 (Navigation-Knowledge Mapping): The navigation-knowledge mapping is a function $M : V_N \longrightarrow 2^{E_K}$ that maps each vertex in G_N (corresponding to a page or page atom) to a set of edges in G_K (corresponding to the collection of knowledge statements presented by the page).

Algorithm 1 shows the pseudo-code for generating navigation graph based on a knowledge graph. As the navigation graph is generated, we also form the navigation-knowledge mapping M. The algorithm runs in time $O(n+md)$, where $n = |V_K|$, $m = |E_K|$, and d is the maximal degree of any node in V_K

Algorithm 1 Create Navigation Graph

createNavigationGraph($G_K\langle V_K, E_K\rangle$, $withFeed$)
  $V_N \leftarrow \emptyset$; $E_N \leftarrow \emptyset$
  for each $v \in V_K$ **do**
    $V_N \leftarrow V_N \cup \{p\}$ //create v's profile page p
    $V_N \leftarrow V_N \cup \{a\}$ //create v's friend list atom a
    for each edge $\langle v, f\rangle \in friends(v)$ **do**
      $M(a) \leftarrow M(a) \cup \{\langle v, f\rangle\}$
    $E_N \leftarrow E_N \cup \{\langle p, a\rangle\}$
  for each $v \in V_N$ **do**
    if v is a friend-list atom **then**
      for each $\langle x, y\rangle \in M(v)$ **do**
        Let $u \in V_N$ be y's profile vertex
        $E_N \leftarrow E_N \cup \{\langle v, u\rangle\}$
  if withFeed = True **then**
    for each vertex $v \in V_K$ **do**
      $V_N \leftarrow V_N \cup \{h\}$ //create homepage
      Let $p \in V_N$ be v's profile vertex
      $E_N \leftarrow E_N \cup \{\langle h, p\rangle\}$
      Let F be a list of v's friends' friendships
      Sort F in non-increasing order by creation time
      for i = 0 to numAtomsPerNewsfeed **do**
        $V_N \leftarrow V_N \cup a_i$
        for j = 0 to numKnowledgePerAtom **do**
          Let $k = \langle x, y\rangle = F.firstItem()$
          $F.remove(k)$
          $M(a) \leftarrow M(a) \cup \{k\}$
          Let $u_x \in V_N$ be x's profile vertex
          Let $u_y \in V_N$ be y's profile vertex
          $E_N \leftarrow E_N \cup \{\langle a_i, u_x\rangle, \langle a_i, u_y\rangle, \langle a_{i-1}, a_i\rangle\}$
  return $G(V_N, E_N)$

IV. Knowledge Exposure

Since users are exposed to knowledge based on visiting pages in the OSN, we first propose to measure page exposures. Once we know exposure value for each page, we can derive exposure values for different pieces of knowledge presented on the pages.

A. Measuring Page Exposure

In order to measure page (and page atom) exposure, we use the PageRank algorithm [15]. While PageRank scores were originally proposed as page importance for ranking search results, they can also be used as estimates for page traffic. PageRank can be interpreted as the behavior of a surfer who randomly follows the hyperlinks on each page (random walk). Such a random surfer may also get bored and jump to a page (without following any specific hyperlink), which is also called *teleportation*. In this setting, the PageRank score can be considered as the traffic or exposure each page receives.

There are some differences between an open web for which PageRank has been proposed and our simplified OSN. Some of the OSN pages such as a user's home page (and news feed) are personalized to the specific user, and are only accessible to that user. Moreover, the teleportation behavior cannot be considered completely random with uniform probability for all pages as in the original PageRank. Fro example. a user cannot jump to the 10th page atom in her news feed without seeing the previous atoms. In order to address these, we adopt the approach of *personalized PageRank* [15] (not for personalization purpose though). In personalized PageRank, the teleportation probabilities are modified to give more weight to the pages in which a specific user is more interested. For our OSN, we set the teleportation probabilities in a way that teleportation can happen only to home pages and with equal probability. In such a setting, we assume that a user would always enter the system by starting at her home page and then navigates to other pages accessible through the hyperlink structure. Also, we assume that all users are equally likely to use the OSN, and as a result all home pages have equal teleportation probability.

We calculate the exposure value for a page or page atom that is represented by vertex $v \in V_N$ by solving the following recursive equation:

$$X(v) = (1-t)X(v)P_N + tT_N \tag{1}$$

where t is the teleportation probability (or damping factor), P_N is the transition matrix for G_N, and T_N is the teleportation distribution. The transition matrix P_N is derived from G_N's adjacency matrix, A_N, where $P_N(i,j) = \frac{A_N(i,j)}{\sum_k A_N(i,k)}$. T_N is a probability distribution vector over V_N, where its elements are equal to $1/u$ for vertices corresponding to home pages (u is the number of users) and zero otherwise.

B. Measuring Knowledge Exposure

The exposure of a knowledge statement is dependent on the exposure of pages on which it appears. Once we know the exposure value for pages in the navigation graph, exposure can be calculated for knowledge statements in the knowledge graph, based on the navigation-knowledge mapping M presented in Section III-C. We calculate the exposure value for a simple knowledge statement represented by edge $e \in E_K$ as

$$X(e) = \sum_{v \in M(e)} X(v) \tag{2}$$

where $X(v)$ denotes corresponding page exposure values calculated according to Equation 1. Furthermore, in order to bound a knowledge exposure value, we normalize it by the sum of all knowledge statement exposure values and denote the result by $\tilde{X}(e)$.

V. Experimental Results

In order to evaluate our proposed exposure model we simulate our simplified OSN using friendship data from a real-world OSN.

A. Dataset

We utilize a 2009 friendship graph collected from Digg [16]. Digg is a social news website that allows users to vote for news content that they deem noteworthy. The graph consists of 279,630 vertices and 1,731,653 edges. Each vertex represents a user, and each edge to represent a friendship between two users. Each edge also has a timestamp, representing the time at which those users became friends.

B. Experiment

The knowledge graph is constructed from the dataset in a one-to-one fashion. That is, for each vertex in the Digg friendship graph, we create a `user` vertex in the knowledge graph, and for each edge in the Digg friendship graph, we create an `isFriendOf` edge in the knowledge graph. We also create `data` nodes corresponding to each user vertex that are connected to `user` nodes using `hasName` edges.

In order to test the effect of news feed on knowledge exposure, we consider two variation of our simplified OSN. The first system, which we call OSN-H, is constructed according to the description in Section II-A. OSN-H contains a home page for each user that includes a news feed presenting the most-recently created friendships among that user's friends. We limit the news feed to 3 atom vertices, each presenting 5 friendships, for a total of 15 friendships per news feed. An investigation of the effects of alternative news feed sizes is left for future work. The second system, which we call OSN-NH, excludes home pages; each user only has a profile page containing all of their friendships, which acts as the user's home page as well. We construct navigation graphs corresponding to each OSN from the knowledge graph, using Algorithm 1, discussed in Section III-C.

Finally, we calculate the exposure scores for pages according to Equation 1. We use an implementation of the PageRank algorithm in the *igraph* library for python to calculate the scores. Specifically, we utilize a personalized PageRank algorithm with two key parameters: the teleportation probability is set to .65, and the destination of any teleport is guaranteed to be a homepage (see Section IV-A) We consider two types of knowledge statements: those about friendship between two users, and those about a user's name. Exposure score for each knowledge statement is calculated based on Equation 2. We normalize friendship and name statements separately, by considering the sum of all friendship exposure values to be 100,000 (as opposed to 1, in order to preserve precision).

In our experiment, we study the followings:

1) The effect of time of friendship formation on the exposure score for a given friendship, and how this differs in OSN-H versus OSN-NH. We expect a more recent friendship to result in a higher score, but only with the existence of news feeds (OSN-H).
2) The relationship between the number of friends that a user has, and the exposure score of that user's name. We expect the name of a user with more friends to have a higher exposure score.
3) The relationship between the number of news feeds that a friendship story appears in, and that friendship's exposure score (Only relevant in case of OSN-H). We expect to observe a correlation between the two.

C. Results and Discussion

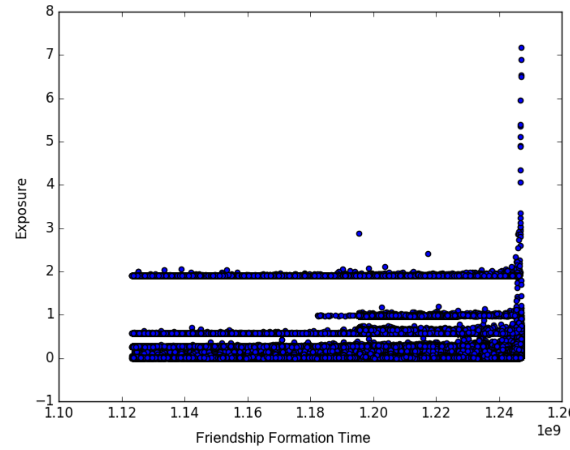
Fig. 5 depicts the exposure values for friendship statements versus the time of friendship formation. There is a weak correlation between creation time and exposure (Pearson correlation of -0.147 and 0.059 for OSN-H and OSN-NH, respectively). Note that y-axis has different scale in Fig. 5a (0 to 8) versus Fig. 5b (0 to 0.45), due to a different range of values in each scenario. Exposure values are much higher in OSN-H, and we hypothesize that this is due to the presence of home pages, which feature more recent friendships. That effect is evident in the difference of exposure values for each friendship statement in the two scenarios (Fig. 5c).

As depicted in Fig. 6, there is a weak correlation between the number of feeds that a friendship appears on and the exposure value for that friendship (Pearson correlation of 0.115). Friendships that appear on more feeds have higher scores.

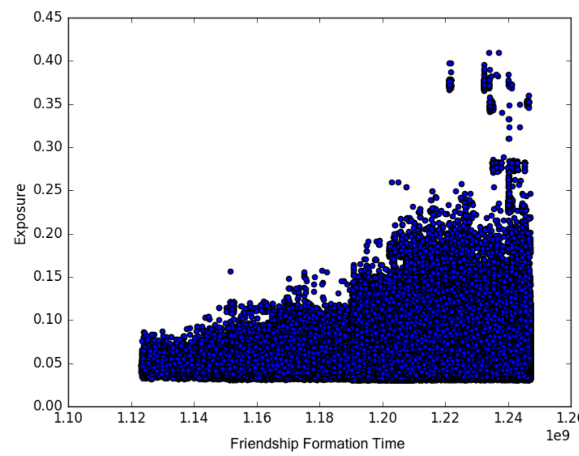
There is also a strong correlation between the number of friends that a user has, and the exposure of that user's name according to the results shown in Fig. 7 (Pearson correlation of 0.804 and 0.955 for OSN-H and OSN-NH, respectively). A user with more friends has a higher name exposure score. We hypothesize that the stronger correlation in OSN-NH is due to the lack of friendship creation time as a factor.

VI. Related Work

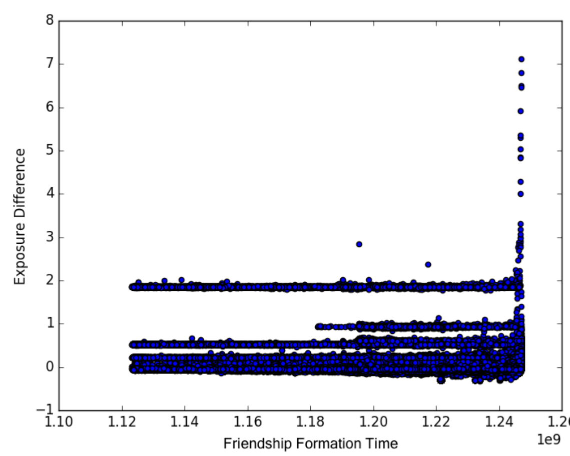
Relationship-based access control policies allow users to constrain access to their data by characterizing their social network relationship with authorized users. The earlier models support constraints on friendship/trust levels and



(a) OSN-H



(b) OSN-NH



(c) Difference between OSN-H and OSN-NH

Figure 5: Friendship Formation Time vs. Exposure

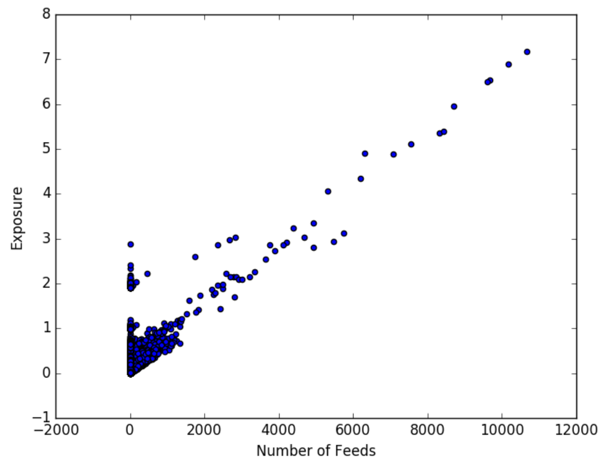
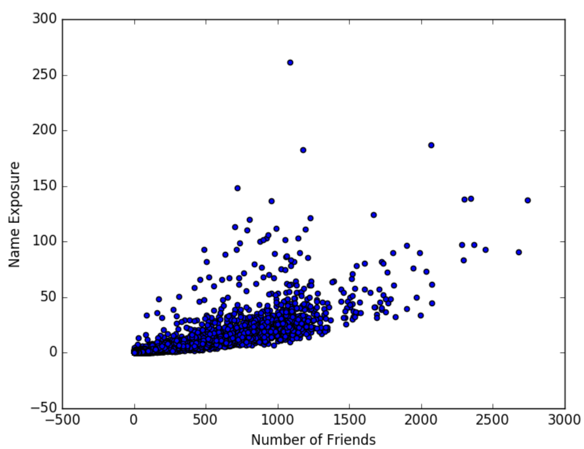
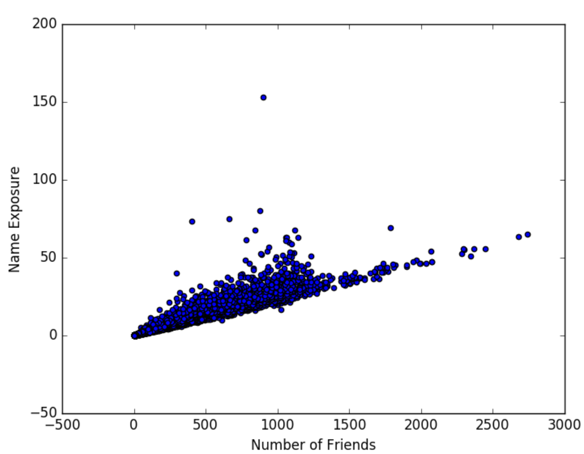


Figure 6: Number of Feeds That a Friendship Appears On vs. Its Exposure



(a) OSN-H



(b) OSN-NH

Figure 7: Number of Friends vs. Exposure of User's Name

distance [4], [17]. Models based on Semantic Web tools allow more expressive [5] and finer-grained policies [6]. More advanced topological social network constraints are formalized and supported by Fong et al. [7], [8]. We propose an exposure measure and approach to calculate it in this work, which is influenced by the user interface design of the OSN, a factor that is not captured in access control policies. Our metric can be used to augment existing access control models for OSNs.

Mondal et al. propose the notion of exposure control as an alternative to access control [14]. They enumerate disadvantage for access control approach for OSN environments, including a priori specification, reliance only on who "can" access, and failing to capture redistribution and inference. They define exposure as the set of principals expected to eventually learn about an information item. As a practical solution, they suggest OSNs use item popularity prediction algorithms [18] in order to predict the exposure of user items. Once users know about the exposures they should be allowed to modify the sharing settings of their items in order to reach desired level of sharing. The high-level solution proposed by Mondal et al. seem to be concerned with the number of times an item is being exposed rather than the actual users who would eventually know about the item (which is their initial definition). Without being able to discern users, such an approach does not seem to be a necessarily better alternative to access control. In contrast, we propose a more concrete and novel exposure measurement approach that considers an OSN's user interface in order to calculate discriminative exposure values for different knowledge statements presented by an OSN.

Link analysis algorithms such as HITS [19] and PageRank [15] propose to calculate importance of pages in a hyperlinked web structure and are primarily used for ranking web search results. While HITS calculates separate hub score (estimating goodness of hyperlinks to other pages) and authority score (estimating goodness of content) for each page, PageRank provides a single importance score for each page. In this work, we adopt a variation of personalized PageRank algorithm in order to calculate the exposure of pages and page atoms.

VII. Conclusion

In this paper, we proposed a knowledge exposure metric as the extent of discoverability of a knowledge statement in an OSN. We proposed our models for knowledge and navigation graphs in an OSN (based on hyperlinked structure of pages). Our metric is essentially calculated by performing link analysis on navigation graph and transferring values to knowledge graph. We also reported our experiment results using a real-world friendship dataset, demonstrating how news feed could affect knowledge exposure in an OSN.

There are several limitations in the present work that we plan to address in the future. We modeled some of the essential features of the current OSNs including hyperlink navigation and dynamically loaded content. However, our current OSN model is still very basic. For example, OSN pages on Facebook have many more elements exposing knowledge to users. A real news feed is also much more complex both in terms of variety of stories presented to users as well as their sorting and selection. We also plan to model more complex and representative knowledge (beyond friendship, names, and profile pictures). In our current exposure measurement model, we did not consider any access constraints imposed by users' privacy settings. Studying the impact of restricted access, e.g., friends-of-friends, will be of our future work. Moreover, we plan to explore how the proposed exposure measurement approach could enhance users' privacy management in OSNs.

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