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Are You My Friend?

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***Abstract*—With Twitters growing popularity, privacy has become a major concern for users wary of sensitive information falling in the wrong hands. A typical Twitter user carries hundreds of followers - people who have subscribed to users twitter feeds. Our goal is to target followers that a Twitter user deems safe. Therefore, selecting followers with a closer relationship could help decrease the risk of sensitive information being sent to unknown people. We propose a privacy management system that helps a Twitter user restrict information to only certain followers based on the strength of their social tie. This system would incorporate two tools: the Exclusivity meter and the Twitter Response Estimator. The Exclusivity Meter employs user's activity profile to guess similarities between users. Preliminary results have indicated that similarity in time and level of activity between user and follower does suggest a stronger social tie. The Twitter Response Estimator uses a measure of prestige to gauge the probability of response. When applied to a set of followers, the estimator separates real friends from recreational followers.**

***Index Terms*—Online social network, Twitter, privacy.**

I. Introduction

With the recent rise of massive online social networks, scholars, political activists, and advertisers have become interested in the nature of social interaction and the propagation of information within such networks. Providers such as MySpace, Facebook, and Twitter, allow users to build a significantly larger social network by increasing the number of individuals they can connect with. These established social connections are typically labeled as ”friends”, ”followers”, or other similar terms. However, as the list of connections expands, it becomes increasingly difficult for users to manage their interactions and preserve the privacy/exclusivity of their shared information. These issues arise because the network embodied by these connections does not represent the actual interactions and relationships that a user maintains with others [1]. Social networks usually weigh each connection equally whereas real social relationships fall under many different classes based on interests, intimacy, work, etc. This leads to privacy problems as certain information may be accessible to the wrong users [2][3][4]. A client or server side application that automatically excludes certain users based on their relevance could greatly reduce privacy concerns.

Furthermore, the sheer number of connections forces most users to focus on only a small number of people that reciprocate attention and are deemed most important. For example, Golder et al. study of Facebook showed that in online social network setting ”friend” has very loose meaning. ”Friend” can be a person whom a user went to school together, met one time at party, or met in online chat room. users only poke and message a small number of people despite having a much larger number of declared ”friends” [5]. A study of social interactions within Twitter reveals that the driver of usage is a sparse and hidden network of connections underlying the ”declared” set of friends and followers. In this paper we will analyze classifying these social ties based on strength of interaction/relationship.

Definition The strength of a tie is a combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services that characterize the tie [6].

The links within a user's general social graph can be split into weak ties and strong ties [6]. Strong ties people such as family, close friends, and people who can affect one's emotional health [7]. Loose acquaintances can be categorized as weak ties. Again, the strength of a tie can be expressed by the following features: communication reciprocity, social overlapping, intimacy, frequency of communication, structure of social graph, and demographic [8]. If the strength of a social tie can be extracted, online social network services can provide users with enhanced functionality to meet demands of privacy and management.

This paper emphasizes specifically the social networking service Twitter. Twitter.com is an online social network used by millions of people around the world to stay connected to their friends, family members and co-workers. The interface allows users to post short messages (up to 140 characters) that can be read by any other Twitter user. Users declare the people they are interested in following, in which case they get notified when that person has posted a new message. A user who is being followed by another user does not necessarily have to reciprocate by following them back, which makes the links of the Twitter social network directed. While all updates are publicly viewable, users can direct status updates to a particular follower. Directed updates are labeled by an ”@” symbol next to the receiver's username in the status message. Data on directed updates becomes crucial in differentiating and classifying social ties in Twitter. *In this paper, we address the following questions: i) Are the targeted followers available? ii) Are they willing to respond? Also, we assume that people with higher social status will not respond often to lesser status people. We found that indeed people with similar activity tend to reply and friends do respond often compared to strangers.*

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In fact many people follow but only friends with higher social tie respond. By limiting the updates to a small number of followers, we can manage the privacy better, reduce overload of updates, and limit nuisance.

II. Problem Definition

This paper addresses the following questions: in the face of information overload, how can Twitter better manage its user's privacy? As mentioned previously, the problem lies with the assumption that all ”friends” within a social network are equal. This assumption precludes the fact that users have different levels of interaction with these ”friends”. In reality, twitter users can place their followers and followees within certain tiers of interaction Fig. 1. Close friends and family can be placed in tier one while distant acquaintances or celebrities fall in the higher tiers. Adding functionality that helps users place followers into such tiers could enhance Twitter's user experience by increasing manageability and privacy. This paper investigates various measures, which gauge the strength of a particular social tie, and then incorporate them into a system that will improve tractability and privacy management for Twitter users.

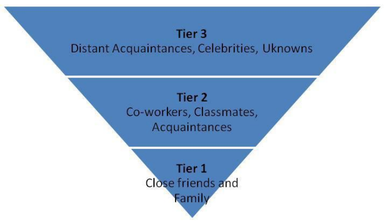


Fig. 1. An example of possible tiers of interaction. A privacy system would use various measures to place followers into such tiers. Placing restrictions on certain tiers lessens the probability of sensitive information being misused.

The system will consist of two tools that deal specifically with manageability: the Exclusivity Meter and Twitter Response Estimator. The Exclusivity Meter targets the most relevant followers. Relevance is based on whether the followers are active at times when users are active. Followers who are online when the user sends a message are more likely to respond at that time. More importantly, similar activity profiles could correlate to a stronger social tie. The paper will study these relationships and build the Exclusivity meter around these studies. Twitter Response Estimator refines this process by computing the willingness of a twitter member to reply to a message from another twitter member. This willingness value, or response estimation, will be based on the prestige indexes of the receiver and sender, the activeness of the receiver, and the level of interaction (direct or indirect) between sender and receiver. By knowing the response estimation of the receiver, the sender can decide whether to proceed with the message.

III. Methodology

1) Build an exclusivity meter to extract a relevant set of followers. This exclusivity meter will help place followers into the various tiers of interaction.
2) Build a response estimator to further refine the set by gauging likelihood of response. We assume that a greater response estimation suggests a closer friend.
3) Incorporate these tools into a privacy setting that restricts information to a targeted set of followers that are deemed safe.

A. Dataset

In this study, we analyze 3,652,148 status updates, 7 users, and 2,305 followers. 2,045 and 1,128 of status updates are reply messages send from user to follower and from follower to user, respectively. Average active account is 276 days, which is calculated by subtracting time stamp of first status–update date from time stamp of last status–update date.

B. Exclusivity Meter

To build the exclusivity meter, we find points of differentiation among followers. On one level, there are two types of followers: followers that have engaged in multiple directed exchanges with the user, and followers who have not. In trying to predict social closeness, sifting through followers who have not had direct exchanges with the user becomes quite challenging. The methodology used to build the exclusivity meter analyzes and quantifies correlations between user activity and follower activity. First, activity profiles based on hourly, daily, and monthly timescales were constructed for both users and followers. Then correlations were calculated between the activity profiles of the users and those of the followers. Finally, all correlation data is totaled and interpreted for meaningful trends that could point to stronger social ties, the idea being that the more correlated the activity profiles, the more likely that the user and the follower share common interests.

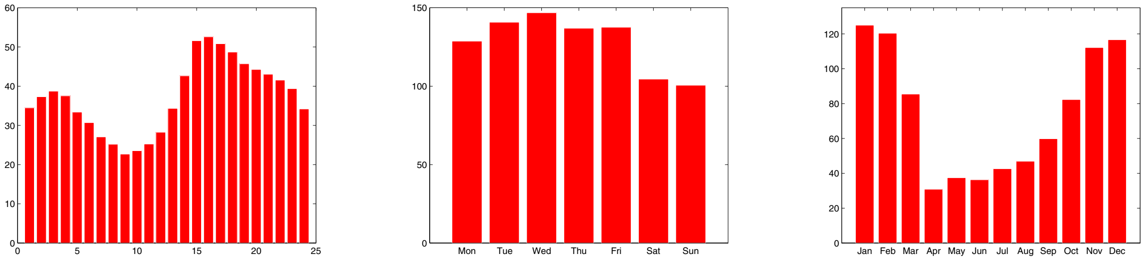
C. Response Estimator

To compute a response estimate, data was collected from Twitter containing information about users. Specific attributes included the following:

1) Number of followers and followees (those the user follows) declared by the user.
2) UserID, screen name, and the utc offset.
3) Status update count for each user (both direct and indirect).
4) Active time since registration.

Definition A member receives many directed ties, but initiates few relations. The prestige index quantifies the popularity of a particular member based on the number of followers and number of followees: $PrestigeIndex = \frac{number of followers}{number of followees}$ By analyzing the relationships between factors such as prestige index and status update counts (for both directed and indirect updates), the paper suggests a possible model for building a Twitter Response Estimator. Central to the analysis will be the added label of ”friend” on particular followers based on the number of directed responses received by those followers.

Definition A friend is defined as any follower that has received two or more directed messages from the user. This is



(a) The Hour Domain

(b) The Week Domain

(c) The Month Domain

Fig. 2. Examples of activity profiles across each time domain.

similar to the first set of followers defined for the exclusivity meter [9]. In addition it is assumed that a friendship exists if follower follows followee and followee follows follower.

The final metric will be response estimation which will be a percentage calculated from prestige index, response type (the frequency of responses over period of activity), and relationship.

IV. Result Analysis

A. Exclusivity Meter

The exclusivity meter seeks to shrink the set of followers to something more tractable in terms of manageability and privacy. The process will use activity profiles to estimate the strength of a tie. The activity profile characterizes user activity on twitter through time and frequency of status-update. We hypothesize that highly correlated activity profiles would suggest a stronger tie between user and follower.

To construct the activity profiles, we plot the number of status updates over different time periods. Fig. 2 shows three examples of activity profiles, one for each time domain. It is evident that there are significant trends within each time domain. Therefore, comparison of user profiles should yield some interesting results.

The first step in the comparison fits the activity profile to a curve. For our interpolation method, we will fit the data points to a polynomial function $p(x)$ of degree six: $p(x) = \sum_{i=1}^{n} p_i x^{n+1-i}$. We believe that the model works well for the comparison because there are relatively few data points, and the curve is flexible enough to accommodate trends. A higher degree was found to oscillate too much and hiding relevant trends. Next, we calculate the integral difference of the functions representing the user and follower profiles: $id_{u,f} = \int_1^N (p_u(x) - p_f(x))dx$. The integral difference enables us to quantify how much the activity profiles between user and follower deviate. The number of intervals in each time domain is denoted by N. The day, week, and year domains have the intervals 24, 7, 12 respectively. Polynomial function $p\_u(x)$ represents the users activity profile data points, and $p_f(x)$ represents the followers activity profile data points. The integral difference, however, only takes into account the amount of deviation between the two curves, neglecting their actual correlations. Therefore we need to measure correlations between two curves. We can calculate a correlation coefficient for each time domain, $cc_{u,f}$. The correlation coefficient shows the strength and linear relationship of the user's and follower's activeness levels, denoted by covariance $cov(u, f)$:

$$cc_{u,f} = \frac{cov(u,f)}{\sigma_u \sigma_f} = \frac{1}{N-1} \sum_{i=1}^{N} (\frac{u_i - \bar{u}}{\sigma_u})(\frac{f_i - \bar{f}}{\sigma_f}), \quad (1)$$

In this equation, the sigmas denote the standard deviations of the user's and follower's activeness levels. The correlation coefficient will always fall between values -1 and 1. The result should be interpreted as follows: $cc_{u,f}$ = 1 high correlation between u and f; $cc_{u,f}$ = 0 no correlation between u and f; and $cc_{u,f}$ = -1 high inverse correlation between u and f.

Together, the integral difference and the correlation coefficient can give a complete relation between user and follower activity profiles. We combined these two measures into a single quantity called the correlation index:

$$ci_{u,f} = cc_{u,f}(1 - \frac{id_{u,f}}{max(id_{u,*})}), \quad (2)$$

The integral difference is normalized by the maximum $abs(id)$ of all the followers to give a consistent result between -1 and 1. A correlation index is calculated for each time domain. However, for purposes of analysis, it is desirable to have a total correlation that quantifies the correlations over all time domains:

$$tci_{u,f} = ci_{u,f}^{hour} + ci_{u,f}^{week} + ci_{u,f}^{month}, \quad (3)$$

The tci is normalized between -1 and 1. tci = 1 suggests a strong relation between the activity profiles of user and its follower. Using tci, we can rank followers based on similarity between user's and the followers activity profiles. An example is shown in Fig. 3 for a particular user and the corresponding followers.

In order to understand the usefulness of the correlation index, we decided to compare this ranking to a control ranking. This control ranking orders the followers based on the amount of responses between the follower and user. The more responses, the stronger the social tie. Therefore, if total correlation index is an effective measure, there should be a strong similarity between the two ranking mechanisms. The

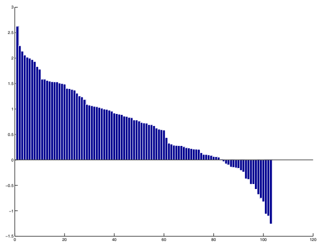


Fig. 3. The x-axis represents followers while the y-axis represents total-correlation. Followers are ranked by correlation.

comparison is achieved by taking the difference of both rankings. If two followers are ranked similarly, their differences should be fairly low. The differences from all users were combined and presented in the histogram Fig. 4. Fig. 4 shows

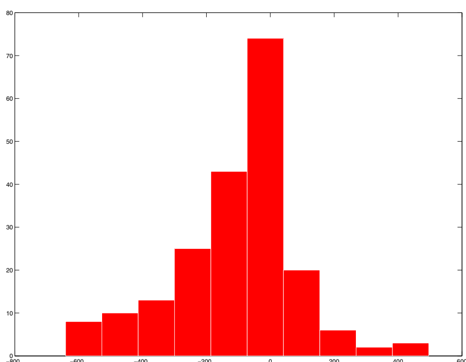


Fig. 4. This histogram demonstrates the difference between our tci ranking method and ranking method based on number of reply status updates. A difference of 0 means both rankings are the same for a particular follower, while a large difference signifies very different rankings. The x-axis represents the difference measure while the y-axis represents number of users with that difference measure. It is evident that ranking methods correlate fairly well, with a large portion of users retaining a small difference measure.

that a significant portion of the followers are ranked similarly by both ranking mechanisms (the difference is close to zero), suggesting that the activeness correlation could provide a useful measure of strength of tie. However, the variance is fairly large, hurting the accuracy. We are improving the ranking system for better accuracy.

B. Response Estimator

The twitter response estimator will take exclusivity a step further by gauging the likelihood of response, thus adding dimensionality to the ranking system in the previous section. Twitter users will usually have a lot more followees than followers. With the average number of followers numbering in the hundreds, a constant stream of twitter feeds would become overwhelming. The simplest filter would be to respond to only those followees who have directed a message directly to the user. The response estimator would sift through a user's set of followees and determine which one would be most likely to respond based on certain statistics.

As mentioned previously, the primary statistic to be incorporated into the response estimator is the prestige index, so the first task would be to better understand the demographics of the twitter population in terms of this prestige index. Fig. 5 displays a distribution of users according to their prestige indexes, with much of the mass lying between prestige indexes 0 and 1. This confirms the intuition that most users will follow

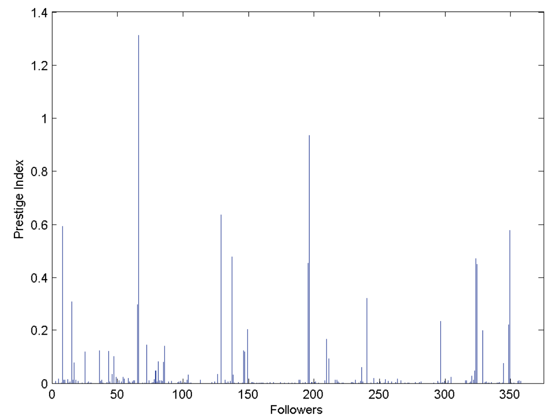


Fig. 5. An example of a user who has 357 followers with their prestige index.

more people than they are being followed by, thus yielding a ratio of less than one. Of course there are users that lie above one, suggesting that they are more popular. For example, there is only one user who has prestige index greater than 1.

It was discussed previously that users will only focus their attention on other members who reciprocate that attention. Based on this idea, an assumption was made as to which followers will most likely be the user's friend. Specifically we assumed that any follower to whom the user directed two or more posts would be considered a friend, while all other followers would be simply considered followers. A measure of response estimation was then used to compare the set of friends with the more general set of followers. Response estimation was calculated as a function of relative prestige index (How much does a users and followers prestige index differ), response frequency, and reciprocity. This probability measure was based on the following assumptions:

1) Let relative prestige index be $\frac{FollowerPrestigeIndex}{UserPrestigeIndex}$. The higher this ratio, the lower the probability of response from the follower.
2) Probability of response is directly related to Update Frequency - the amount that a follower updates within a given period of time.
3) A reciprocal tie between two twitter users suggests greater probability of response than a directed (one-way) tie.

Next, we test the performance of response estimator against different friend definitions by changing number of direct messages sent from user, shown in Fig. 6. Although there is slight accuracy decline as we use tightly defined rules for friend definition, performance is fairly high between 97% and 93%. Saddle point x = 16 indicates that number of direct messages sent from user to the follower are usually less than 16, which demonstrates that the Twitter is mainly used for broadcasting information. We can define the accuracy of response estimator equal to 93%. We further analyze response

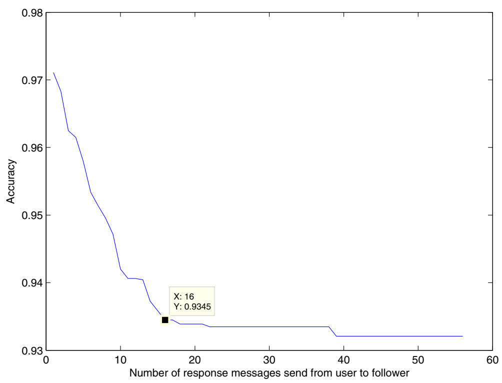


Fig. 6. Accuracy of response estimator is shown with different friend definitions.

estimator with friend definition 2 (two or more messages sent from user to follower) in Table I. Only 5% of followers can fit for this definition. Although some users have many followers, they contact with very small percentage of the followers. The nature of the Twitter network is that one can follow anyone which may explain this phenomena. TP, TN, FP, and FN stands for true positive, true negative, false positive, and false negative, respectively. As we can see the method works well

TABLE I

FRIENDSHIP DEDUCTION BASED ON RESPONSE ESTIMATOR. WE COMPARE THE PERFORMANCE OF RESPONSE ESTIMATOR COMPARED TO TWITTER DEFINITION OF A FRIEND (E.G., AT LEAST TWO RESPONSES FROM A FOLLOWER SUGGEST A SIGN OF FRIENDSHIP).

	Followers	Friends	TP	TN	FP	FN
User 1	103	22	17	80	1	5
User 2	220	2	1	217	1	1
User 3	410	1	0	409	0	1
User 4	317	5	4	311	1	1
User 5	174	2	2	167	5	0
User 6	357	35	30	297	25	5
User 7	724	46	44	656	22	2

for few hundreds of followers but the accuracy decays with large number of followers. Though false positives are only 3-5%, still large in numbers. We are investigating on other methods suitable for very large number of followers (e.g., several thousands)

V. CONCLUSION

The methods proposed by both the response estimator and the exclusivity meter rely on calculating a measure of strength of the tie between a user and follower. Given a definition for ”friend” (such as a follower with two or more directed responses), response estimation and activity levels correlate highly with followers that are considered friends. These two tools form the basis of a system that could enhance privacy of twitter feeds by restricting information to a relevant set of followers.

Much of the challenge in undertaking this analysis lay in the data collection process. Future work will deal with the design of the proposed tools based on the results of this paper. However, this paper suggests several unanswered questions that would prove crucial in using these studies in a privacy system. Further tests are required to adequately understand the significance of the activity correlation measure. Our ranking method suggests a relationship between activity and response frequency. But the variance in the results indicates that other validation methods would be useful.

Currently several users have setup the configuration such that when somebody registers to follow them, they automatically follow the follower. This artificially balloons up the list of followers. The end goal is to identify real friends who will respond compared to recreational followers. Another goal to give the user better control over the broadcast of their status-updates. Mechanisms proposed would most likely be automatic. Default settings could limit the extent of a broadcast to those followers that the system deems safe (based on various metrics). This would ensure a default privacy setting that can handle sensitive information in a more intelligent manner.

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