ABSTRACT

With the popularity of Social Networking Services (SNS), more and more sensitive information are stored online and associated with SNS accounts. The obvious value of SNS accounts motivates the usage stealing problem—unauthorized, stealthy use of SNS accounts on the devices owned/used by account owners without any technology hacks. For example, anxious parents may use their kids' SNS accounts to inspect the kids' social status; husbands/wives may use their spouses' SNS accounts to spot possible affairs. Usage stealing could happen anywhere in any form, and seriously invades the privacy of account owners. However, there is no any currently known defense against such usage stealing. To an SNS operator (e.g., Facebook Inc.), usage stealing is hard to detect using traditional methods because such attackers come from the same IP addresses/devices, use the same credentials, and share the same accounts as the owners do.

In this paper, we propose a novel continuous authentication approach that analyzes user browsing behavior to detect SNS usage stealing incidents. We use Facebook as a case study and show that it is possible to detect such incidents by analyzing SNS browsing behavior. Our experiment results show that our proposal can achieve higher than 80% detection accuracy within 2 minutes, and higher than 90% detection accuracy after 7 minutes of observation time.

1. INTRODUCTION

Many people use Social Networking Services (SNS, such as Facebook) daily, and have associated a lot of personal and sensitive information with their SNS accounts. These information generally include friend lists, feeds from their friends, non-public posts/photos, private interactions with others (such as chats and messages), purchased apps/items, etc., and its obvious value makes the SNS accounts one of the most targeted online resources by hackers to steal. To protect user privacy, SNS sites today have done a lot to prevent account stealing. For example, Facebook records the regular IP addresses and devices used by each account. If an account logs in with an unusual IP address or device, the account is prompted to either answer some secret questions [1] or enter a security code sent to the account owner’s mobile device [2] in order to verify if the login is authentic. Facebook also allows users to report account stealing manually if they suspect that their accounts have been stolen.

Despite of all the efforts to prevent account stealing, user privacy can also be compromised by another form of breach called usage stealing—unauthorized, stealthy use of SNS accounts on the devices owned/used by account owners without any technology hacks. Usage stealing could happen anywhere in any form. For example, anxious parents may use their kids' SNS accounts to inspect the kids' social status; husbands/wives may use their spouses' SNS accounts to spot possible affairs. Similarly, colleges, supervisors, friends, or siblings, just to name a few, may also have their own motives to use acquaintances’ accounts for different reasons.

Usage stealing is common in practice due to the following reasons. First, when using their own computers, people tend to choose “yes” when the browsers ask whether they would like to save their (SNS) passwords for automatic logins in the future. This is especially true when users are using their mobile devices because it is cumbersome to input passwords [22, 13]. Mobile devices also ease the usage stealing in other aspects, in that they can be physically accessed by acquaintances or strangers [29], and that most of them are not locked by PINs [10]. In addition, many SNS sites use cookies to save the trouble of future account authentications within a short time. For example, once logged into Facebook, a user need not login again during at most 60 following days [5]. From the above, if someone (mostly an acquaintance) can access the computer or mobile devices of an SNS user, it is likely that the person, without the need of technical background, can peep the information associated with the SNS account.

However, there is no any currently known defense against such usage stealing. To an SNS site, usage stealing is hard to detect using traditional methods because the attackers come from the same IP addresses/devices, use the same credentials, and share the same accounts as the owners do. Moreover, because users normally do not see the logs, victims can hardly sense and report the stealthy usage.

Contributions. In this paper, we identify the usage stealing problem in SNS and propose a novel continuous authentication approach [19, 20] that analyzes users’ browsing behavior to detect usage stealing incidents. We use Face-
book as a case study, and show that it is possible to detect such incidents by analyzing their browsing behavior on the SNS sites, namely, clicks on newsfeed, friend lists, profiles, likes, messages, photos/videos, and comments. Our user study shows that our proposed scheme can achieve above 80% accuracy with a high confidence within 2 minutes, and higher than 90% accuracy after 7 minutes of observation time.

Deployment. Our detection approach is designed to run on SNS servers and to serve as the first line of defense against account usage stealing. The deployment is straightforward: an SNS server collects the behavior of an account’s session and feeds it into a detection model in real time. The model determines whether the user of the session is suspicious, and if so, the SNS server can either 1) trigger more sophisticated analysis/monitoring, and/or 2) challenge the session user immediately by secret questions or via a second channel such as mobile phone authentication. Note that since we are at the first line of defense, there is no need for an 100% accurate detection model, rather, a reasonable detection power is sufficient and the key is a prompt and efficient detection. Also, please note that the proposed methodology is neither tied to a specific SNS site nor to a certain learning technique as it is based on the standard supervised learning framework. For example, while we adopt the smooth SVM as the detection model in this paper, the service operators (e.g., Facebook Inc.) may choose the asymmetric SVM or similar methods if they wish to further reduce the false positive rates.

Implications. We believe that the usage stealing problem, while not being well studied so far, will be much more critical in the future, as people put more and more sensitive information online. In fact, this problem may not only occur in the social services, but also online email services such as Gmail and Outlook.com, time management services such as Google Calender and Remember The Milk, photo album services such as Instagram, and much more. Except asking users to repeatedly authenticate themselves (practically prohibited by usability issues), continuous authentication seems to be the only feasible solution for attacks of this kind.

The rest of this paper is organized as follows. We review the related work in Section 2. Section 3 discusses the rationale behind detecting usage stealing based on browsing behavior. In Section 4, we describe our user study on Facebook and analyze the users’ behavior. Section 5 elaborates our detection methodology. We evaluate the performance of our scheme in Section 6 and analyze the security issues in Section 7. Finally, Section 8 concludes the paper.

2. RELATED WORK

In this section, we review existing studies on the privacy issues on SNS and continuous authentication.

SNS Privacy. Privacy is always a concern for SNS users. Many efforts have been devoted to protect user privacy. He et al., Zheleva et al., and Tang et al. observe a privacy hole that attackers can infer private information (such as sexual orientation) of a user from his/her public SNS records/activities. Felt et al. and Wishart et al. prevent privacy leaks from SNS developer APIs and from the software based on them. Mahmood et al. focus on another type of privacy attacks called the frequent account deactivation. Meanwhile, in the industry, Facebook takes a vector of measures to protect user privacy. For example, it provides an official page to educate users about the correct privacy and security settings, and records the IP addresses, web browsers, and devices used by each account. If an account logs-in with unknown records, Facebook will challenge the user either by secret questions or via mobile phone authentication. Facebook also allows users to report account stealing incidents manually.

However, none of the above attempts can protect user privacy when the attackers sneak in using the same devices owned by the victims. Since the passwords, credentials, and cookies are usually stored in users’ devices to avoid repeated account authentication, attackers who have physical access to these devices can easily bypass all the above detection schemes and obtain the sensitive information associated with the SNS accounts.

Continuous Authentication. Continuous authentication is an implicit, automatic re-authentication method that analyzes the follow-up user actions after his/her initial authentication to make sure if the user is still authentic. The actions can be keyboard typing behavior, mouse movements, operations on mobile devices, facial characteristics (if a webcam is available), or any other soft biometric traits. However, the above analyses are per-person-based; that is, a detection model is required for each user. This may be cost-prohibitive on SNS servers given that an SNS site usually have more than millions of users. The continuous authentication method proposed in this paper analyzes web browsing behavior performed by only three predefined user groups. The detection model is universal to all users and it introduces low data collection and computation overhead. Another advantage of our proposal is that the scheme can be applied to a new account whose associated biometric behavior is not yet clear. Note that our proposal is not a replacement for existing continuous authentication approaches. Rather, it can serve a low-cost filter for suspicious accounts, with which the servers can trigger more sophisticated, personalized analysis whenever necessary.

3. RATIONALE BEHIND OUR DETECTION APPROACH

Nowadays, an SNS service such as Facebook is not merely a place for people to maintain their friend lists. They are more like a platform where people engage various social activities, such as posting own status, reading others’ comments on news, chatting, and meeting new people, etc. Studies show that there is no typical user behavioral pattern on a complicated, open platform like Facebook, as every single user seems to have his/her own behavioral tendency on an SNS service. For example, some people tend to fulfill their desire on self-presentation, so they spend most time on sharing their own latest status and posting the latest photos/events. In the meantime, some people may manage to engage new friends online; some chat with familiar friends; some spend time discovering new social games; and some others like to stalk certain other users.

1A Facebook newsfeed, which locates at the center column of one’s home page, is a constantly updated list summarizing the status of people that one follows on Facebook.

2For example, Facebook has more than a billion monthly active users as of December 2012.
Given the diversity in user behavioral patterns determined by users’ personal characteristics and social status, it is hard to profile every user’s browsing behavior when they are using an SNS service. However, we argue that users would normally exhibit significantly different behavior when they are browsing their own and others’ pages.

In the context of usage stealing, each user can have one of the three following roles when using an SNS service: 1) owner, when he/she is using his/her own account; 2) acquaintance (as a stalker), when he/she is using the account of someone he/she knows; and 3) stranger (as a stalker), when he/she is using the account of an unknown person. Intuitively, when checking the Facebook newsfeed as the owner, a user would focus more on the latest information of friends and use the “like” or “share” function to interact with others. On the other hand, when browsing a newsfeed as a stalker (either an acquaintance or a stranger), the user may be interested in earlier information that is more interesting to the stalker. He/she may not interact with others because he/she does not want the owner to discover the stealthy usage later. In summary, we believe that users would normally behave differently at different roles because

- The way people treat familiar information (or information from familiar friends) would be different than the way they treat unfamiliar information;

- People at different roles would have different intentions;

- In order not to be found by the account owners, people as the stalkers may behave differently with the time pressure.

We call the above differences in users’ browsing behavior as the role-driven behavioral diversity. We conjecture that Facebook users, as well as users of the other SNS services, possess such diversity, and this serves as the main rationale behind our detection scheme.

In the following, we shall prove that the role-driven behavioral diversity indeed exists using the datasets we collect in a user study on Facebook (Section 4) and then show that our detection scheme can rely on this property to classify account owners from stalkers (Section 5).

4. FACEBOOK USER BEHAVIOR

We use Facebook as a case study on users’ role-driven behavior.

4.1 Data Collection

To capture the role-driven behavioral diversity, we hire a number of Facebook users to be our subjects and design experiments in which subjects browse Facebook newsfeed at different roles. In other words, we ask each subject to browse 1) his/her own newsfeed, 2) his/her friend’s newsfeed, and 3) a stranger’s newsfeed.

To conduct the experiment, we hire pairs of subjects from an one-million-user Internet community. Each pair of subjects must be with at least one of the following relationships: friends, family members, colleagues, classmates, and couples. Each subject is paid 10 USD and we get the subject’s permission to record all actions (e.g., clicks, typing, page views, etc.) he/she performs when browsing a newsfeed. A subject is hired only if he/she is an active Facebook user—the subject must have more than 50 friends and consistently stay on Facebook longer than 4 hours per week.

Each experiment comprises 3 rounds. In each round, a subject is asked to browse the newsfeed of an account (either of his/her, his/her friend’s, or a stranger’s own) for 30 minutes. The subjects and accounts are paired randomly; overall, each subject is guaranteed to browse his/her own account, the account of acquaintance, and an account of stranger in the three rounds with a randomized order.

![Figure 1: (A, B) and (C, D) are pairs of acquaintances. Each experiment comprises 3 rounds. In each round, each subject is assigned to an account randomly; overall, each subject is guaranteed to browse his/her own account, the account of acquaintance, and an account of stranger in the three rounds with a randomized order.](image)

| Property          | Value          |
|-------------------|----------------|
| # experiments     | 28             |
| Total time        | 9302 min       |
| # subjects        | 112            |
| # male subjects   | 56             |
| # female subjects | 44             |
| # sessions        | 278            |
| # self-usage      | 100            |
| # acquaintance-usage | 81        |
| # stranger-usage  | 97             |
| Avg. session length | 30 min      |
| Avg. action rate  | 3.0 action/min |
| Avg. page switching rate | 0.7 page/min |

Table 1: A summary of the experiments and raw dataset.
Next, we define a number of features and obtain their values for every session we collect so that the machine learning algorithms can be applied. Even we have a perfect learning algorithm, without features that encode information about who is controlling a session, the algorithm will have no way to distinguish the account owners from stalkers. How to define features that we need is a key issue in this work, and is usually challenging because it requires insights, domain knowledge, creativity, and even “black arts”.

We interview heavy users of Facebook about their regular usage patterns and the ways they discover and explore interesting information. Based on the results, we define 139 features. All the features of a particular session can be extracted from the session’s action list (see Table 3). Our features can be basically summarized as follows:

1. \( f.<\text{action}> \): the frequency of a certain action (per minute). The \(<\text{action}>\) can be any action defined in Table 2. We also keep \( f.\text{acts} \) and \( f.\text{acts}.\text{excluding. page.expand} \), the frequencies of all actions and all actions except the “expand page” action respectively. The reason we capture the latter feature is that we want to determine how much a user really does in addition to merely browsing pages.

2. \( f.<\text{target_type},<\text{action}> \): the frequency of a certain action targeting a certain target user type. The \(<\text{action}>\) is an interactive action in Table 2 and \(<\text{target_type}>\) can be self (if the target person is the account owner), friend (if the target person is a friend of the account owner), or nonfriend (if the target person is not a friend).

3. \( b.<xxx> \): the binary version of all the above features; i.e., \( b.<xxx> = 1 \) if \( f.<xxx> \) is greater than 0. For example, \( b.<\text{action}> \) denotes whether or not a certain action occurs during the session.

4. \( f.\text{act}.<\text{target_type}> \): the frequency of all interactive actions performed on a certain target user type.

5. \( t.\text{page}.<\text{page_type}> \): the time the session user spends on a certain page type. The \(<\text{page_type}>\) can be feed (the account’s newsfeed), msg (the account’s message box), self (pages, such as the wall/friend list/note/photos, of the account owner), friend (pages of friends), nonfriend (pages of non-friends), or public (fans or groups pages).

6. \( f.\text{act}.\text{page}.<\text{page_type}> \): the frequency of all actions performed on a certain page type. We also keep \( f.\text{act}.\text{expand.page}.<\text{page_type}> \) and \( f.\text{act}.\text{non.expand.page}.<\text{page_type}> \), the frequencies of the “expand page” action and all other actions performed on a certain page type respectively.

7. \( n.\text{act.person} \): the number of target people the user interacts with during the session.

8. \( n.\text{act.person}.<\text{statistics}> \): the statistics of the counts of visits to different users’ pages during the session. The \(<\text{statistics}>\) include mean, standard deviation.

In Facebook, some pages (e.g., newsfeeds, walls, etc.) and page items (e.g., comments, notifications lists, etc.) are expandable. For clarity, these pages/items show earlier/detailed information only upon expansion.

| Actions                | Interactive | Page-Switching |
|------------------------|-------------|----------------|
| Expand Comments        | ✓           |                |
| Likes                  | ✓           |                |
| View Cards             | ✓           |                |
| View Likes             | ✓           |                |
| View Messages          | ✓           |                |
| View Photos            | ✓           |                |
| To Friend List Page    | ✓           | ✓              |
| To Note Page           | ✓           | ✓              |
| To Photo Page          | ✓           | ✓              |
| To Wall Page           | ✓           | ✓              |
| To Fan Page            | ✓           |                |
| To Feed Page           | ✓           |                |
| To Group Page          | ✓           |                |
| To Message Page        | ✓           |                |
| Add Comments           | ✓           |                |
| Delete Comments        | ✓           |                |
| Click Hyper-links      | ✓           |                |
| Expand Page            | ✓           |                |

Table 2: 18 types of common user actions we collected on Facebook.

| Time stamp | Action       | Target Person |
|------------|--------------|---------------|
| 1345837539249.47 | Likes | Friend A |
| 1345837568519.15  | View Cards | Account Owner |
| 1345837863398.26  | Add Comment | Friend A |
| 1345837732512.73  | Group page | |
| 1345837756445.03  | Likes | Friend B |
| 1345837770260.55  | View Cards | Non-Friend C |
| 1345837773293.04  | View Message | Friend A |
| 1345837825998.01  | Likes | Non-Friend C |
| 1345837875240.45  | Expand Page | |

Table 3: An exemplar list of the collected actions.
4.3 Role-Driven Behavioral Diversity

To justify the existence of the role-driven behavioral diversity between the account owners, acquaintances, and strangers, we carry out some analysis of the user behavior performed at different roles. Our observations are summarized as follows.

**General Diversity.** As shown in Figure 2(a), all sessions controlled by the three user roles have similar values in \( f_{\text{acts}} \). However, in \( f_{\text{acts.excluding.page.expand}} \) (Figure 2(b)), the sessions controlled by the account owners exhibit higher values than those by the acquaintances, which in term give higher values than those by strangers. This implies that the acquaintances/strangers usually pay more attention to reading/searching for interesting information. They also care more about earlier information, as the content hidden by expandable pages/items by default are older.

The sessions used by acquaintances/strangers also yield much lower values in \( f_{\text{act.add.comment}} \) (Figure 2(c)) and \( f_{\text{act.like}} \) (Figure 2(d)) than those by the account owners. The reason is obvious: Acquaintances/strangers normally do not want to leave a clue of their peeping behavior.

**What Stalkers Do Not Care.** Although the acquaintances/strangers expand pages more frequently (Figure 2(b)), they do not expand the comment lists as commonly as the account owners do. This is because the acquaintances/strangers may not know the people leaving the comments, therefore showing less interest to them. Due to similar reasons, acquaintances/strangers also express less interests in the fans/groups pages (Figure 2(e)) and who likes a post (Figure 2(f)); in addition, they also spend less time in the accounts’ newsfeeds (Figure 2(g)). In particular, strangers tend to ignore most of the newsfeeds because they generally do not know people whose information appear in the feeds (Figure 2(h)).

**What Acquainted Stalkers Care.** As compared with the other roles, the acquaintances pay more attention to the accounts’ friend lists (Figure 2(i)). This is because an acquaintance may know the account owner’s friends and be curious about these friends’ status (especially the status of those people who are not currently a friend of the acquaintance). The acquaintances are generally more interested in the message boxes (Figure 2(j)) and the profile cards of the accounts’ friends (Figure 2(k)) due to similar reasons.

**What Stranger Stalkers Care.** Interestingly, the account owners’ profiles (Figure 2(l)) and photos (Figure 2(m)) are most viewed by strangers rather than the account owners’ friends or the owners themselves. This is because the strangers do not know the account owners, so they are usually curious about who the owners are and how they look like. The strangers are also less affected by the account owners’ social relationship. For example, they are more willing to check out non-friends (Figure 2(n)) and external links (Figure 2(o)).

We believe that the above findings suffice to prove the existence of the role-driven behavioral diversity. Next, we show how this diversity can be further utilized to implement a low-cost detector for usage stealing.

5. DETECTION SCHEME

This section introduces a scheme for detecting the usage stealing on SNS sites.

In our dataset, each session is labeled with either “account owner,” “acquaintance,” or “stranger.” Since our goal is to distinguish stalkers from the account owners, in the following, we replace the “acquaintance” and “stranger” labels with a single “stalker” label.

Figure 3 gives an overview of our detection scheme. After a user starts a session (by either logging-in newly or using existing authentication cookies, Step 1), the SNS server monitors and collects a list of actions performed by the user for an observation period of \( n \) minutes, where \( n \) is a configurable parameter (Step 2). After the observation period, the SNS server extracts the features of the monitored session based on the recorded action list (Step 3), where the features are defined in Section 4.2. It then feeds the session features into a detection model (Step 4), which determines whether the session owner is suspicious by predicting the label of the session (Step 5). If the predicted label is “stalker,” the SNS server can challenge the user by secret questions or via a second channel such as mobile phone authentication (Step 6). Alternatively, the server can trigger a more sophisticated (but costly) detection scheme.

Note that the scheme has low runtime cost on an SNS server because it requires only one detection model for all SNS users, taking the advantage of the role-driven behavioral diversity. Also note that, although we employ a two-class detection model to distinguish stalkers from the account owners, the scheme can be readily extended to identify the account owners, acquaintances, and strangers if a multi-class detection model is adopted.

We obtain our detection model by training it using the labeled sessions we collected. Clearly, the effectiveness of our detection scheme largely depends on the quality of predictions made by the detection model. In order to obtain high-quality predictions, we take rigorous steps in training the model, as summarized below.
shows that the margin equals two inequations), as shown in Figure 4. Simple calculation between negative instances in the hyperplane $\{w^\top x + b \geq 1\}$ for some $w \in \mathbb{R}^d$ and $b \in \mathbb{R}$, and then find $w$ and $b$ such that the hyperplane $\{x : w^\top x + b = 0\}$ separates the positive and negative instances.\footnote{In practice, the training dataset $D$ usually contains instances that are noises or outliers (i.e., instances with wrong labels). To tolerate these instances, the SVM does not insist the positive and negative instances to be placed exactly at the two sides of the margins. It introduces a slack variable $\xi_i$, $\xi_i \geq 0$, for each instance $x_i$ in $D$ and requires only $y_i(w^\top x_i + b) \geq 1 - \xi_i$. So noises and outliers can be placed inside the margin or even at opposite sides. This gives the objective of linear SVM:

$$\arg\min_{w,b,\xi} \|w\|_2^2 + C \sum_{i=1}^n \xi_i$$

s.t. $y_i(w^\top x_i + b) \geq 1 - \xi_i$ and $\xi_i \geq 0$, for $i = 1, 2, \ldots, n.$}

$$\sum_{i=1}^n \xi_i$$

in order to penalize the noises and outliers and keep their numbers small. The hyperparameter $C$ controls the trade-off between maximizing the margin and minimizing the number of noises/outliers.\footnote{The linear SVM can be extended to nonlinear SVM by utilizing the kernel trick. Define a function $\phi : \mathbb{R}^d \to \mathbb{R}^{d'}$ that maps an instance $x$ to a point in a higher (possibly infinite) dimensional space, the nonlinear SVM finds a separating hyperplane in that space. Since $d' > d$, the found hyperplane may not be linear anymore in the original $d$-dimensional input space. It can be shown that, if we choose $\phi$ carefully such that the inner product $\phi(a)^\top \phi(b)$ can be represented by a kernel function $K : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ (i.e., $\phi(a)^\top \phi(b) = K(a,b)$) for any $a, b \in \mathbb{R}^d$, then we can solve the objective of nonlinear SVM in a manner whose

\begin{align}
\arg\min_{w,b,\xi} \|w\|_2^2 & + \sum_{i=1}^n \xi_i
\end{align}
complexity is independent of the higher dimension $d'$. This is known as the kernel trick. The nonlinear SVM usually makes better predictions than the linear SVM does when the input dimension $d$ is not very high.

**Practical Considerations.** The objective of conventional SVM (either linear or nonlinear) can be solved by standard quadratic programming software. However, when applied to an SNS service like Facebook, the solver needs to deal with an extremely large $D$ due to the huge user base owned by the SNS service. To speed up the training process, we adopt the Smooth SVM (SSVM) \[14\] in this paper. The SSVM, a variant of SVM, adds $\frac{\nu^2}{2}$ into the objective of SVM and employs the squares of slacks $\xi_i^2$ to penalize the noises/outliers. The SSVM utilizes the KKT optimization condition to convert the conventional SVM to an unconstrained minimization problem that can be solved efficiently using the Newton’s method with an Armijo stepsize.

The kernel trick applies to the SSVM too. In our experiment, we pair up the nonlinear SSVM with the RBF kernel, which is defined as $K(a, b) = e^{-\gamma \|a-b\|^2}$.

There are 2 hyperparameters we have to determine in the nonlinear SSVM: the penalty coefficient $C$ and $\gamma$ in the RBF kernel function. We use the uniform design model selection method \[12\] with 9-13 stages to search for an appropriate combination of these hyperparameters.

### 5.2 Feature Selection

The training of SSVM is preceded by a feature selection process \[25\], where we select only a subset of features in $D$ for the training. This process is necessary because 1) given a tremendous amount of sessions (Figure 2) that will be monitored by the SNS servers, it helps the SSVM scale up in making predictions by considering only a small set of features; 2) the selected features give us a hint on what is useful to distinguish the stalkers from the account owners. By ignoring those features that are not helpful, we can collect fewer actions (Figure 3.2) and save the cost of feature extraction (Figure 3.3) on each SNS server; and 3) our results show that it improves the prediction accuracy of the final SSVM we obtain.

The feature selection process is divided into two stages, as shown in Figure 5. In the first stage, we use the 1-norm SVM \[31\] to determine a candidate set of features. In the second stage, we use the forward feature selection \[25\] algorithm to determine the best final features from the candidate set for training the detection model.

Unlike the SVM which minimizes $|w|^2$ in its objective (Eq. 2), the 1-norm SVM minimizes $|w|^2$ (called the LASSO penalty \[23\]) instead. We employ the 1-norm SVM to determine the candidate set because it usually finds a sparse $w$ (i.e., $w$ that tends to have zeros) thanks to its “compressed sensing” interpretation \[8\]. We obtain the candidate set by keeping only those features that correspond to the non-zeros in $w$, as the features corresponding to zeros are usually redundant or noise features \[31\].

And then, we use the forward feature selection algorithm to determine the final features from the candidate set. The algorithm starts with an empty set for keeping the final features. At each step, one feature from the candidate set that improves the prediction accuracy of SSVM most is added to this set. The algorithm then repeats the above step until the candidate set becomes empty or there is no feature in the candidate set that improves the accuracy.

### 6. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed detection model.

#### 6.1 Settings and Metrics

After data cleaning (described in Section 4.1), there are 278 instances (i.e., sessions) in $D$, among which 178 instances are positive (i.e., labeled by +1, which denotes “acquaintance” or “stranger”) and 100 instances are negative (i.e., labeled by −1, which denotes “account owner”). Each instance is presented by 139 feature values.

To the best of our knowledge, currently there is no other detection scheme for the usage stealing problem in SNS services. Thus we compare the detection model to itself by imposing different observation periods. Specifically, given an observation period $L$, we extract the feature values of a session only from those actions that are performed within $L$ minutes after the start of the session. We study the performance of the detection model given $L = 1, 2, \cdots, 25$ minutes. Although a subject was asked browse an SNS account for 30 minutes during each round of the experiment described in Section 4.1, we set the maximal value of $L$ to 25 rather than 30 because some subjects appear to lose patience and become idle after 25 minutes. Under the premise of data consistency, we consider $L \leq 25$ here.

As described in Sections 5.2 and Section 5.1, to obtain our detection model, we first employ the 1-norm SVM to get the candidate features, and then use the forward feature selection and SSVM with 10-fold cross validation to find the best

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Figure 5: The steps in training a detection model.
Table 4: The confusion matrix.

|                | With Oversampling | Without Oversampling |
|----------------|-------------------|----------------------|
| Feature        | Acc: 93.53%       | Acc: 90.29%          |
| Selection      | FPR: 5.00%        | FPR: 18.00%          |
| F-score         | 0.9483            | 0.9260               |
| Without Feature| Acc: 91.37%       | Acc: 87.77%          |
| Selection      | FNR: 10.11%       | FNR: 6.74%           |
| F-score         | 0.9302            | 0.9071               |

Table 5: The results achieved under various conditions.

We first study the performance of our detection model when $L = 25$ minutes. Table 7 shows the results achieved by the model with and without feature selection. As we can see, feature selection does improve the performance by giving higher accuracy/F-scores and lower FPR/FNR. This is because the noisy features are successfully eliminated. Figure 7 shows that there are only 60 features remain after the applying the 1-norm SVM for candidate set selection.

We notice that the dataset $D$ is imbalanced—the ratio of positive instances to negative ones is 1.78 : 1. Since there are more positive than negative instances, we tend to obtain a higher FPR. To overcome this issue, we adopt an oversampling approach by randomly selecting and duplicating 78 negative instances to balance the ratio between positive and negative instances. The effect of duplicating an instance is to double the penalty if we misclassify the instance. So by duplicating negative instances in $D$ we can avoid aliasing and reduce the FPR. Note that because there exists randomness when applying the oversampling technique, we train 10 models and average their results. Table 6 shows the results achieved by our model with and without oversampling. We can see that the oversampling successfully controls the trade-off between FPR and FNR.

Figure 7 shows the ROC curve and AUC of our model when both the feature selection and oversampling are applied. We get a fairly high AUC (0.962). In particular, the ROC curve shows that we can achieve 90% TPR at 4.5% FPR.

6.2 Detection Performance at 25 Minutes

We first study the performance of our detection model when $L = 25$ minutes. Table 7 shows the results achieved by the model with and without feature selection. As we can see, feature selection does improve the performance by giving higher accuracy/F-scores and lower FPR/FNR. This is because the noisy features are successfully eliminated. Figure 7 shows that there are only 60 features remain after the applying the 1-norm SVM for candidate set selection.

We notice that the dataset $D$ is imbalanced—the ratio of positive instances to negative ones is 1.78 : 1. Since there are more positive than negative instances, we tend to obtain a higher FPR. To overcome this issue, we adopt an oversampling approach by randomly selecting and duplicating 78 negative instances to balance the ratio between positive and negative instances. The effect of duplicating an instance is to double the penalty if we misclassify the instance. So by duplicating negative instances in $D$ we can avoid aliasing and reduce the FPR. Note that because there exists randomness when applying the oversampling technique, we train 10 models and average their results. Table 6 shows the results achieved by our model with and without oversampling. We can see that the oversampling successfully controls the trade-off between FPR and FNR.

Figure 7 shows the ROC curve and AUC of our model when both the feature selection and oversampling are applied. We get a fairly high AUC (0.962). In particular, the ROC curve shows that we can achieve 90% TPR at 4.5% FPR.

6.3 Early Detection Performance

To prevent the leak of sensitive information, we should perform the usage stealing detection as early as possible for each session. To see how our model performs with time limits, we vary $L$ from 1 to 25 minutes and train respective models for each $L$ with feature selection and oversampling. Figure 8 shows the accuracy achieved by these models. After 7 minutes, we can get stable and reasonably good results, with the accuracy rate higher than 90% with $L \geq 7$ minutes. Even at 2 minutes, we obtain an accuracy above 80%, which is still satisfactory when the scheme is used as a trigger for more sophisticated analysis.
Figure 8: Accuracy for every minute. It shows that our detection model can achieve stable and reasonably good results after 7 minutes.

Figure 9: The accuracy achieved by 20 models trained using the 10-fold cross validation on 20 randomly permuted datasets. The thick line represents the average accuracy.

To test the robustness of our model, we randomly permute $D$ for 20 times and train one model using the 10-fold cross validation [25] for each of the 20 permutations. Figure 9 and Table 6 show the mean accuracy and standard deviation given by the 20 models. The results indicate that the accuracy has a very low standard deviation regardless of $L$. In addition, comparing Figure 9 with Figure 8, we can see that our model performs consistently no matter it is trained (using the 10-fold cross validation) or tested (using the leave-one-out cross validation), which means the performance of our detection scheme is very robust.

7. SECURITY ANALYSIS

As shown in Figure 8, all the data collection, processing, decision, and follow-up actions (such as challenges and punishment) in our scheme can all be performed on the server side. So there is no way for attackers to compromise the scheme from the clients.

Since our detection methodology is running at the server side (i.e., at operators), the attackers cannot evade our detection scheme—once logged-in, each user (including the attacker) must be monitored by an SNS server running our scheme. The only way for an attacker to continuously use the victim’s account is to evade the detection model.

The detection model does not rely on any cryptography technology and is completely user-behavior-based. So, in order not to be detected by the model, attackers have to 1) mimic the owners’ actions; or 2) do as few actions as possible and run away. The attackers of the first kind are less likely because the owner’s action model is not well known [13]. Even if some attackers read this paper and successfully mimic the owners, they are forced to spend time on something they are not really interested and skip some information they desire more. This makes the attacks less harmful. For the attackers of the second kind, our scheme imposes a high time pressure because the detection model can achieve close to 80% accuracy even if an attackers browse the victims’ newsfeeds for only 1 minute. Again, the time pressure makes the attacks less harmful because the attackers may not be able to find the information they want within such a limited time.

Note that our detection scheme is not tied to any specific detection model. For example, a personalized detection model can be particularly helpful to identify the attackers of the first kind because it is even harder to imitate each individual’s behavior. Also, a detection model that takes the timestamp of each action into account may be helpful to identify the attackers of the second kind, because users (either the account owners or stalkers) often take actions in some order they are used to. In fact, while this work firstly points out a new direction for future research against the usage stealing, it is certainly possible to develop more sophisticated detection models to fight against the ever-smarter attackers.

8. CONCLUSION

In this paper, we have proposed a novel continuous authentication approach for SNS that analyzes users’ browsing behavior to detect usage stealing incidents. We use Facebook as a case study and show that 1) the role-driven behavioral diversity does exist; 2) based on the so-called role-driven behavioral diversity property, we can design a low-cost detection scheme applicable to all users; and 3) the scheme is hard to evade and it renders reasonable detection performance after an observation period of 2 minutes.

As future work, we plan to study the browsing behavior of individuals and develop personalized detection models.
These models can be triggered only when needed and serve as the detailed analyzers for suspicious sessions. We also plan to improve our low-cost detection model to give higher detection accuracy within the first 7 minutes. Such an improvement is possible because we see different user behavior in short- and long-term. To share our observation, we counted features corresponding to the 3 most positive and 3 most negative weights in w identified by SSVM when the observation period L varies from 1 to 7. Figures 10 and 11 show the histograms of counts of the 3 most positively- and negatively-weighted features respectively. Some features are rather surprising as they are not prominent in the full 30-minute traces discussed in Section 4.3. We hope this study can motivate in-depth studies on developing more sophisticated models against usage stealing issues.

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