

Towards Detecting Compromised Accounts on Social Networks

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Abstract

Compromising social network accounts has become a profitable course of action for cybercriminals. By hijacking control of a popular media or business account, attackers can distribute their malicious messages or disseminate fake information to a large user base. The impacts of these incidents range from a tarnished reputation to multi-billion dollar monetary losses on financial markets. In our previous work, we demonstrated how we can detect large-scale compromises (i.e., so-called campaigns) of regular online social network users. In this work, we show how we can use similar techniques to identify compromises of individual high-profile accounts. High-profile accounts frequently have one characteristic that makes this detection reliable – they show consistent behavior over time. We show that our system, were it deployed, would have been able to detect and prevent three real-world attacks against popular companies and news agencies. Furthermore, our system, in contrast to popular media, would not have fallen for a staged compromise instigated by a US restaurant chain for publicity reasons.

Index Terms—Online Social Networks, Cybercrime, Network Security

1 Introduction

Online social networks, such as Facebook and Twitter, have become one of the main media to stay in touch with the rest of the world. Celebrities use them to communicate with their fan base, corporations take advantage of them to promote their brands and have a direct connection to their customers, while news agencies leverage social networks to distribute breaking news. Regular users make pervasive use of social networks too, to stay in touch with their friends or colleagues and share content that they find interesting.

Over time, social network users build trust relationships with the accounts they follow. This trust can develop for a variety of reasons. For example, the user might know the owner of the trusted account in person or the account might be operated by an entity commonly considered as trustworthy, such as a popular news agency. Unfortunately, should the control over an account fall into the hands of a cyber criminal, he can easily exploit this trust to further his own malicious agenda. Previous research showed that using compromised accounts to spread malicious content is advantageous to cyber criminals, because social network users are more likely to react to messages coming from accounts they trust [1].

These favorable probabilities of success exceedingly attract

the attention of cyber criminals. Once an attacker compromises a social network account he can use it for nefarious purposes such as sending spam messages or link to malware and phishing web sites [2]. Such traditional attacks are best carried out through a large population of compromised accounts belonging to regular social network account users. Recent incidents, however, demonstrate that attackers can cause havoc and interference even by compromising individual, but high-profile accounts. These accounts (e.g., newspaper or popular brand name accounts) have large social circles (i.e., followers) and their popularity suggests trustworthiness to many social network users. Recent attacks show that compromising these high profile accounts can be leveraged to disseminate fake news alerts, or messages that tarnish a company’s reputation [3], [4], [5], [6].

Moreover, the effects of an account compromise can extend well beyond the reputation of a company. For example, the dissemination of an erroneous Associated Press (AP) news story about a bomb exploding in the White House in 2013 led to a 1% drop in the Standard & Poor’s 500 index, temporarily wiping out US\$ 136B [7]. Compromises of high profile accounts usually get cleaned up quickly after they are detected. Unfortunately, since detection is still exclusively a manual endeavor, this is often too late to mitigate the negative impacts of account compromises. For example, the above mentioned AP message was shared by over 3,000 users before the compromise was detected and the offending message

removed. Similarly, a message sent as a consequence of a compromise of the Skype Twitter account happening during a national holiday remained accessible for over a day [6]. These incidents show that it is critical for a social network to be able to reliably detect and block messages that have not been authored by an account’s legitimate owner.

A wealth of research was proposed in the last years to detect malicious activity on online social networks. Most of these systems, however, focus on detecting fake accounts specifically created to spread malicious content, instead of looking for legitimate accounts that have been compromised [8], [9], [10]. These systems are inadequate to detect compromised accounts, because legitimate, yet compromised accounts have significantly different characteristics than fake ones. Other mitigation techniques have a more general scope, and either detect malicious accounts by grouping together similar messages [11], [12] or by looking at the presence of suspicious URLs in social network messages [13], [14]. These systems can detect messages that are sent by compromised social network accounts, in case cybercriminals use multiple accounts to send similar messages, or the messages are used to advertise web pages pointing to malware or phishing. In the case of the high-profile compromises mentioned before, however, neither of these conditions apply: the compromises each consisted of a single message, and no URLs were contained in any of the messages. Therefore, previously-proposed systems are inadequate to detect this type of compromises.

In this paper we present COMPA, the first detection system designed to identify compromised social network accounts. COMPA is based on a simple observation: social network users develop habits over time, and these habits are fairly stable. A typical social network user, for example, might consistently check her posts in the morning from her phone, and during the lunch break from her desktop computer. Furthermore, interaction will likely be limited to a moderate number of social network contacts (i.e., friends). Conversely, if the account falls under the control of an adversary, the messages that the attacker sends will likely show anomalies compared to the typical behavior of the user.

To detect account compromises, COMPA builds a behavioral profile for social network accounts, based on the messages sent by the account in the past. Every time a new message is generated, the message is compared against this behavioral profile. If the message significantly deviates from the learned behavioral profile, COMPA flags it as a possible compromise. In this paper we first show that high profile accounts often have well-defined behavioral profiles that allow COMPA to detect compromises with very low false positives. However, behavioral profiles of regular user accounts are more variable than their well-defined counterparts of most high profile accounts. This is because regular users are more likely to experiment with new features or client software to engage with the social network. This variability could cause an increase of false positive alerts. However, social network accounts of regular users are less influential than high profile

accounts. Thus, attackers aggregate multiple accounts into a *campaign* to achieve effects that are similar to the compromise of a high profile account. COMPA uses this insight to first identify campaigns by means of message similarity and only labels accounts as compromised if a significant portion of messages in a campaign violate the behavioral profile of their underlying account. This allows us to keep false positives low, while still being able to detect accounts that are victims of large-scale compromises.

To evaluate COMPA, we applied it to four Twitter compromises that affected high profile accounts over the last three years. We show that our system would have been able to detect those malicious messages before they were posted, avoiding the fake information to spread. We also show a case study of a compromise that was faked by the Chipotle Twitter account for promotional reasons; in this case COMPA correctly detected that the alleged malicious messages did not deviate from the regular behavior of the account. Finally, we also applied COMPA to two datasets from Twitter and Facebook, looking for large-scale compromises. The Twitter dataset consists of 1.4 billion messages we collected from May 13, 2011 to August 12, 2011, while the Facebook dataset contains 106 million messages ranging from September 2007 to July 2009 collected from several large geographic networks. Our results show that COMPA is effective in detecting compromised accounts with very few false positives. In particular, we detected 383,613 compromised accounts on Twitter, and 11,087 compromised accounts on Facebook.

In summary, this paper makes the following contributions:

- We present COMPA, the first system designed to detect compromised social network accounts.
- We show that COMPA can reliably detect compromises that affect high profile accounts. Since the behavior of these accounts is very consistent, false positives are minimal.
- To detect large-scale compromises, we propose to group similar messages together and apply COMPA to them, to assess how many of those messages violate their accounts’ behavioral profile. This grouping accounts for the fact that regular social network accounts show a more variable behavior compared to high profile ones, and allows us to keep false positives low.
- We apply COMPA to two datasets from popular social networks, Facebook and Twitter, and show that our system would have been able to detect hundreds of thousands of compromised accounts. We also show that COMPA would have been able to detect four high-profile compromises that affected popular Twitter accounts, and to correctly flag as legitimate a fake compromise that was attempted by a US fast food chain on their Twitter account for promotional reasons.

Comparison with previous published version. This paper is the extended version of our previous work [15] that was

published at the Network and Distributed Systems Security Symposium in 2013. Compared to the original paper, in which we focused on large-scale compromises that affect thousands of social network accounts at the same time, in this paper we also look at isolated compromises that affect high-profile accounts. We show that such accounts typically show a very consistent behavior, and therefore COMPA can reliably detect compromises against them. To demonstrate this, we analyzed four compromises of high-profile accounts that made the news during the past three years, showing that COMPA would have detected them.

2 Background: Social Network Compromises

In the following, we illustrate four case studies where high-profile Twitter accounts were compromised. We will use these case studies to both show how critical a social network compromise can be for a company, as well as how our system could be used to detect and ultimately prevent such attacks.

Associated Press. On April 23rd 2013, the Twitter account of the Associated Press (@AP) was compromised [4]. The account was misused to distribute false information about president Obama being hurt by an explosion in the White House. This message had an interesting side effect: seconds after being posted, it was used as a signal of negative events by automated trading bots on the New York stock exchange. This signal led to a perceivable drop in the market index which recovered after the information was confirmed to be false [7]. This incident shows how a social network compromise can have significant effects on the real world.

FoxNews Politics. On July 4th 2011, the Twitter account of Fox News' politics (@foxnewspolitics) division got compromised [3]. The attackers used this opportunity to distribute the information that president Obama got assassinated.

Skype. On new year's day 2014, the Twitter account of the Skype Voip service was compromised. The attacker used his access to discourage the use of Microsoft's email products for the fear of disclosing information to government agencies. We would assume that an observant legitimate owner of the account would detect such a malicious message during their regular activity. However, presumably because of the holiday season, it took more than two hours before the offending message was removed by the legitimate owners of the Skype account. In the meantime, the offending message got retweeted over 8,000 times. This incident prominently demonstrates the advantages an automated technique for the detection of compromised accounts would entail, as such attacks can have significant negative impact on a brand's online reputation.

Yahoo! News. More recently, in August 2014, Yahoo!'s news account (@YahooNews) also got compromised and used to disseminate false information regarding an Ebola outbreak in Atlanta, GA.

To prevent social network accounts from being compro-

mised, we propose to learn the typical behavior of a user, and flag a message as a possible compromise if it does not match the learned behavior. In the following section, we describe in detail the behavioral profile that we leverage as part of our system. In Section 7.4 we provide details on the anomalies generated by the four described high-profile incidents, which allowed COMPA to detect them.

3 Behavioral Profiles

A behavioral profile leverages historical information about the activities of a social network user to capture this user's normal (expected) behavior. To build behavioral profiles, our system focuses on the stream of messages that a user has posted on the social network. Of course, other features such as profile pictures or social activity (e.g., establishing friend or follower relationships) could be useful as well. Unfortunately, social networks typically do not offer a way to retrieve historical data about changes in these features, and therefore, we were unable to use them.

A behavioral profile for a user U is built in the following way: Initially, our system obtains the stream of messages of U from the social networking site. The message stream is a list of all messages that the user has posted on the social network, in chronological order. For different social networks, the message streams are collected in slightly different ways. For example, on Twitter, the message stream corresponds to a user's public timeline. For Facebook, the message stream contains the posts a user wrote on her own wall, but it also includes the messages that this user has posted on her friends' walls.

To be able to build a comprehensive profile, the stream needs to contain a minimum amount of messages. Intuitively, a good behavioral profile has to capture the breadth and variety of ways in which a person uses her social network account (e.g., different client applications or languages). Otherwise, an incomplete profile might incorrectly classify legitimate user activity as anomalous. Therefore, we do not create behavioral profiles for accounts whose stream consists of less than a minimum number S of messages. In our experiments, we empirically determined that a stream consisting of less than $S = 10$ messages does usually not contain enough variety to build a representative behavioral profile for the corresponding account. Furthermore, profiles that contain less than S messages pose a limited threat to the social network or its users. This is because such accounts are either new or very inactive and thus, their contribution to large scale campaigns is limited. A detailed discussion of this threshold is provided in our previous work [15].

Once our system has obtained the message stream for a user, we use this information to build the corresponding behavioral profile. More precisely, the system extracts a set of feature values from each message, and then, for each feature, trains a statistical model. Each of these models captures a characteristic feature of a message, such as the time the

message was sent, or the application that was used to generate it. The features used by these models, as well as the models themselves, are described later in this section.

Given the behavioral profile for a user, we can assess to what extent a new message corresponds to the expected behavior. To this end, we compute the anomaly score for a message with regard to the user's established profile. The anomaly score is computed by extracting the feature values for the new message, and then comparing these feature values to the corresponding feature models. Each model produces a score (real value) in the interval $[0, 1]$, where 0 denotes perfectly normal (for the feature under consideration) and 1 indicates that the feature is highly anomalous. The anomaly score for a message is then calculated by composing the results for all individual models.

3.1 Modelling Message Characteristics

Our approach models the following seven features when building a behavioral profile.

Time (hour of day). This model captures the hour(s) of the day during which an account is typically active. Many users have certain periods during the course of a day where they are more likely to post (e.g., lunch breaks) and others that are typically quiet (e.g., regular sleeping hours). If a user's stream indicates regularities in social network usage, messages that appear during hours that are associated with quiet periods are considered anomalous.

Message Source. The source of a message is the name of the application that was used to submit it. Most social networking sites offer traditional web and mobile web access to their users, along with applications for mobile platforms such as iOS and Android. Many social network ecosystems provide access to a multitude of applications created by independent, third-party developers.

Of course, by default, a third-party application cannot post messages to a user's account. However, if a user chooses to, she can grant this privilege to an application. The state-of-the-art method of governing the access of third-party applications is OAUTH [16]. OAUTH is implemented by Facebook and Twitter, as well as numerous other, high-profile web sites, and enables a user to grant access to her profile without revealing her credentials.

By requiring all third-party applications to implement OAUTH, the social network operators can easily shut down individual applications, should that become necessary. In fact, our evaluation shows that third-party applications are frequently used to send malicious messages.

This model determines whether a user has previously posted with a particular application or whether this is the first time. Whenever a user posts a message from a new application, this is a change that could indicate that an attacker has succeeded to lure a victim into granting access to a malicious application.

Message Text (Language). A user is free to author her messages in any language. However, we would expect that each user only writes messages in a few languages (typically, one or two). Thus, especially for profiles where this feature is relatively stable, a change in the language is an indication of a suspicious change in user activity.

To determine the language that a message was written in, we leverage the `libtextcat` library. This library performs n-gram-based text categorization, as proposed by Cavnar and Trenkle [17]. Of course, for very short messages, it is often difficult to determine the language. This is particularly problematic for Twitter messages, which are limited to at most 140 characters and frequently contain abbreviated words or uncommon spelling.

Message Topic. Users post many messages that contain chatter or mundane information. But we would also expect that many users have a set of topics that they frequently talk about, such as favorite sports teams, music bands, or TV shows. When users typically focus on a few topics in their messages and then suddenly post about some different and unrelated subject, this new message should be rated as anomalous.

In general, inferring message topics from short snippets of text without context is difficult. However, some social networking platforms allow users to label messages to explicitly specify the topics their messages are about. When such labels or tags are available, they provide a valuable source of information. A well-known example of a message-tagging mechanism are Twitter's *hashtags*. By prefixing the topic keyword with a hash character a user would use `#Olympics` to associate her tweet with the Olympic Games. Using hashtags to identify topics in messages have become so popular that Facebook decided in August 2013 to incorporate this feature unmodified.

More sophisticated (natural language processing) techniques to extract message topics are possible. However, such techniques are out of scope of this work.

Links in Messages. Often, messages posted on social networking sites contain links to additional resources, such as blogs, pictures, videos, or news articles. Links in messages of social networks are so common that some previous work has strongly focused on the analysis of URLs, often as the sole factor, to determine whether a message is malicious or not. We also make use of links as part of the behavioral profile of a user. However, in our system the link information only represents a single dimension (i.e., feature) in the feature vector describing a message. Moreover, recall that our features are primarily concerned with capturing the normal activity of users. That is, we do not attempt to detect whether a URL is malicious in itself but rather whether a link is different than what we would expect for a certain user.

To model the use of links in messages, we only make use of the domain name in the URL of links. The reason is that a user might regularly refer to content on the same domain. For example, many users tend to read specific news sites and blogs, and frequently link to interesting articles there.

Similarly, users might have preferences for a certain URL shortening service. Of course, the full link differs among these messages (as the URL path and URL parameters address different, individual pages). The domain part, however, remains constant. Malicious links, on the other hand, point to sites that have no legitimate use. Thus, messages that link to domains that have not been observed in the past indicate a change. The model also considers the general frequency of messages with links, and the consistency with which a user links to particular sites.

Direct User Interaction. Social networks offer mechanisms to directly interact with an individual user. The most common way of doing this is by sending a direct message that is addressed to the recipient. Different social networks have different mechanisms for doing that. For example, on Facebook, one posts on the recipient user’s wall; on Twitter, it is possible to directly “mention” other users by putting the @ character before the recipient’s user name. Over time, a user builds a personal interaction history with other users on the social network. This feature aims to capture the interaction history for a user. In fact, it keeps track of the users an account ever interacted with. Direct messages are sent to catch the attention of their recipients, and thus are frequently used by spammers.

Proximity. In many cases, social network users befriend other users that are geographically or contextually close to them. For example, a typical Facebook user will have many friends that live in the same city, went to the same school, or work for the same company. If this user suddenly started interacting with people who live on another continent, this could be suspicious. Some social networking sites (such as Facebook) express this proximity notion by grouping their users into networks. The proximity model looks at the messages sent by a user. If a user sends a message to somebody in the same network, this message is considered as local. Otherwise, it is considered as not local. This feature captures the fraction of local vs. non-local messages.

4 Training and Evaluation of the Models

In a nutshell, COMPA works as follows: for each social network user, we retrieve the past messages that the user has authored. We then extract features for each message, and build behavioral models for each feature separately. Then, we assess whether each individual feature is anomalous or not, based on previous observations. Finally, we combine the anomaly scores for each feature to obtain a global anomaly score for each message. This score indicates whether the account has likely been compromised. In the following, we describe our approach in more detail.

Training. The input for the training step of a feature model is the series of messages (the message stream) that were extracted from a user account. For each message, we extract the relevant features such as the source application and the domains of all links.

Each feature model is represented as a set \mathbf{M}_f . Each element of \mathbf{M}_f is a tuple $\langle fv, c \rangle$. fv is the value of a feature (e.g., *English* for the language model, or *example.com* for the link model). c denotes the number of messages in which the specific feature value fv was present. In addition, each model stores the total number N of messages that were used for training.

Our models fall into two categories:

- *Mandatory* models are those where there is one feature value for each message, and this feature value is always present. Mandatory models are *time of the day*, *source*, *proximity*, and *language*.
- *Optional* models are those for which not every message has to have a value. Also, unlike for mandatory models, it is possible that there are multiple feature values for a single message. Optional models are *links*, *direct interaction*, and *topic*. For example, it is possible that a message contains zero, one, or multiple links. For each optional model, we reserve a specific element with $fv = \text{null}$, and associate with this feature value the number of messages for which no feature value is present (e.g., the number of messages that contain no links).

The training phase for the *time of the day* model works slightly differently. Based on the previous description, our system would first extract the hour of the day for each message. Then, it would store, for each hour fv , the number of messages that were posted during this hour. This approach has the problem that strict one hour intervals, unlike the progression of time, are discrete. Therefore, messages that are sent close to a user’s “normal” hours could be incorrectly considered as anomalous.

To avoid this problem, we perform an adjustment step after the *time of the day* model was trained (as described above). In particular, for each hour i , we consider the values for the two adjacent hours as well. That is, for each element $\langle i, c_i \rangle$ of \mathbf{M}_f , a new count c'_i is calculated as the average between the number of messages observed during the i^{th} hour (c_i), the number of messages sent during the previous hour (c_{i-1}), and the ones observed during the following hour (c_{i+1}). After we computed all c'_i , we replace the corresponding, original values in \mathbf{M}_f .

As we mentioned previously, we cannot reliably build a behavioral profile if the message stream of a user is too short. Therefore, the training phase is aborted for streams shorter than $S = 10$, and any message sent by those users is not evaluated.

Evaluating a new message. When calculating the anomaly score for a new message, we want to evaluate whether this message violates the behavioral profile of a user for a given model. In general, a message is considered more anomalous if the value for a particular feature did not appear at all in the stream of a user, or it appeared only a small number of times.

For *mandatory features*, the anomaly score of a message is calculated as follows:

- 1) The feature fv for the analyzed model is first extracted from the message. If \mathbf{M}_f contains a tuple with fv as a first element, then the tuple $\langle fv, c \rangle$ is extracted from \mathbf{M}_f . If there is no tuple in \mathbf{M}_f with fv as a first value, the message is considered anomalous. The procedure terminates here and an anomaly score of 1 is returned.
- 2) As a second step, the approach checks if fv is anomalous at all for the behavioral profile built for the feature under consideration. c is compared to \bar{M}_f , which is defined as $\bar{M}_f = \frac{\sum_{i=1}^{\|\mathbf{M}_f\|} c_i}{N}$, where c_i is, for each tuple in \mathbf{M}_f , the second element of the tuple. If c is greater or equal than \bar{M}_f , the message is considered to comply with the learned behavioral profile for that feature, and an anomaly score of 0 is returned. The rationale behind this is that, in the past, the user has shown a significant number of messages with that particular fv .
- 3) If c is less than \bar{M}_f , the message is considered somewhat anomalous with respect to that model. Our approach calculates the relative frequency f of fv as $f = \frac{c_{fv}}{N}$. The system returns an anomaly score of $1 - f$.

The anomaly score for *optional features* is calculated as:

- 1) The value fv for the analyzed feature is first extracted from the message. If \mathbf{M}_f contains a tuple with fv as a first element, the message is considered to match the behavioral profile, and an anomaly score of 0 is returned.
- 2) If there is no tuple in \mathbf{M}_f with fv as a first element, the message is considered anomalous. The anomaly score in this case is defined as the probability p for the account to have a `null` value for this model. Intuitively, if a user rarely uses a feature on a social network, a message containing an fv that has never been seen before for this feature is highly anomalous. The probability p is calculated as $p = \frac{c_{null}}{N}$. If \mathbf{M}_f does not have a tuple with `null` as a first element, c_{null} is considered to be 0. p is then returned as the anomaly score.

As an example, consider the following check against the *language* model: The stream of a particular user is composed of 21 messages. Twelve of them are in English, while nine are in German. The \mathbf{M}_f of the user for that particular model looks like this:

$(\langle \text{English}, 12 \rangle, \langle \text{German}, 9 \rangle)$.

The next message sent by that user will match one of three cases:

- The new message is in English. Our approach extracts the tuple $\langle \text{English}, 12 \rangle$ from \mathbf{M}_f , and compares $c =$

12 to $\bar{M} = 10.5$. Since c is greater than \bar{M}_f , the message is considered normal, and an anomaly score of 0 is returned.

- The new message is in Russian. Since the user never sent a message in that language before, the message is considered very suspicious, and an anomaly score of 1 is returned.
- The new message is in German. Our approach extracts the tuple $\langle \text{German}, 9 \rangle$ from \mathbf{M}_f , and compares $c = 9$ to $\bar{M}_f = 10.5$. Since $c < \bar{M}_f$, the message is considered slightly suspicious. The relative frequency of German tweets for the user is $f = \frac{c}{N} = 0.42$. Thus, an anomaly score of $1 - f = 0.58$ is returned. This means that the message shows a slight anomaly in the user average behavior. However, as explained in Section 6.2, on its own this score will not be enough to flag the message as malicious.

Computing the final anomaly score. Once our system has evaluated a message against each individual feature model, we need to combine the results into an overall anomaly score for this message. This anomaly score is a weighted sum of the values for all models. We use Sequential Minimal Optimization [18] to learn the optimal weights for each model, based on a training set of instances (messages and corresponding user histories) that are labeled as malicious and benign. Of course, different social networks will require different weights for the various features. A message is said to violate an account’s behavioral profile if its overall anomaly score exceeds a threshold. In Section 4.1, we present a more detailed discussion on how the features and the threshold values were calculated. More details, including a parameter sensitivity analysis on the threshold value, are presented in our previous work [19], [20]. Moreover, we discuss the weights (and importance) of the features for the different social networks that we analyzed (i.e., Twitter and Facebook).

Robustness of the Models. In our original paper we show that it is difficult for an attacker to mimic all the behavioral models used by COMPA [15]. In addition, in our setup we only used features that are observable from the outside — if COMPA was deployed by a social network instead, they could use additional indicators, such as the IP address that a user is connecting from or the browser user agent.

Novelty of the modelled features. In our previous paper [15] we show that most of the features used by COMPA are novel, and were not used by previous work. In addition, existing systems focus on detecting fake accounts, and therefore look for similarities across different accounts to flag them as malicious. In COMPA, conversely, we look for changes in the behavior of legitimate accounts.

4.1 Training the Classifier

As discussed in Section 4, COMPA uses a weighted sum of feature values to determine whether a new message violates the behavioral profile of its social network account. Naturally,

this bears the question how to determine optimal feature weights to calculate the weighted sum itself. To determine the feature weights in COMPA, we applied Weka’s SMO [21] to a labeled training dataset for both Twitter and Facebook. A detailed discussion how we prepared the training datasets can be found in our previous work [15]. Note that this dataset is different than the one used to evaluate COMPA in Section 7.

While on Facebook, at the time of our experiment, we could easily infer a user location from her geographic networks, Twitter does not provide such a convenient proximity feature. Therefore, we omitted this feature from the evaluation on Twitter. For Twitter, the weights for the features are determined from a labeled training dataset consisting of 5,236 (5142 legitimate, 94 malicious) messages with their associated feature values as follows: *Source* (3.3), *Personal Interaction* (1.4), *Domain* (0.96), *Hour of Day* (0.88), *Language* (0.58), and *Topic* (0.39).

On Facebook, based on a labeled training dataset of 279 messages (181 legitimate, 122 malicious), the weights were: *Source* (2.2), *Domain* (1.1), *Personal Interaction* (0.13), *Proximity* (0.08), and *Hour of Day* (0.06). Weka determined that the *Language* feature has no effect on the classification. Moreover, as discussed earlier, assessing the message topic of an unstructured message is a complicated natural language processing problem. Therefore, we omitted this feature from the evaluation on the Facebook dataset.

5 Behavioral Profile Stability

Detecting deviations in account behavior is simplified if the commonly occurring behavior follows mostly regular patterns. Thus, in this section we ask (and answer) the question of whether there is a class of social network accounts that are particularly amenable to such an analysis. Arguably, a social network strategy is a crucial part for the public relation department of most contemporary companies. Intuitively, we would expect a well managed company account to show a more stable behavior over time than accounts operated by regular users. To assess whether this intuition is valid we conducted an experiment and evaluated the message streams of popular companies for behavioral profile violations. As positive example of social network compromises, we considered the four high-profile incidents described previously. As a baseline comparison we also evaluated the message streams of randomly chosen social network accounts.

5.1 Popular Accounts

To assess whether the behavioral profiles of popular accounts are indeed mostly stable over time we performed the following experiment. Alexa [22] is a service that ranks popular websites. We assume that most popular websites are operated by popular businesses. Thus we identify the Twitter accounts that correspond to the top 5 entries in each of 16 categories ranked by Alexa (e.g., arts, news, science, etc.). Additionally, we add the Twitter accounts that correspond to the top 50 entries of

#	Twitter Account	Violations (%)	#	Twitter Account	Violations (%)
1	163	0%	40	derspiegel	2%
2	alibabatak	0%	41	espn	2%
3	ap	0%	42	imgur	2%
4	bloombergnews	0%	43	msnbc	2%
5	bostonglobe	0%	44	tripadvisor	2%
6	bw	0%	45	twitch	2%
7	ebay	0%	46	xe	2%
8	ehow	0%	47	yahoosports	2%
9	engadget	0%	48	walmart	2%
10	expedia	0%	49	bing	3%
11	forbes	0%	50	nfl	3%
12	foxnews	0%	51	reverso_	3%
13	foxnewspolitics	0%	52	blizzardcs	4%
14	gsmaarena_com	0%	53	google	4%
15	huffingtonpost	0%	54	linkedin	4%
16	imdb	0%	55	yahoofinance	4%
17	latimes	0%	56	cnn	5%
18	lemondefr	0%	57	timeanddate	5%
19	msn	0%	58	yandexcom	5%
20	nbnews	0%	59	urbandictionary	5%
21	nytimes	0%	60	netflix	6%
22	pchgames	0%	61	weebly	6%
23	reuters	0%	62	stumbleupon	7%
24	skype	0%	63	yahooanswers	7%
25	stackfeed	0%	64	reddit	9%
26	steam_games	0%	65	yelp	9%
27	washingtonpost	0%	66	instagram	10%
28	yahoo	0%	67	youtube	10%
29	9gag	1%	68	nih	12%
30	amazon	1%	69	ancestry	13%
31	digg	1%	70	microsoft	13%
32	eL_pais	1%	71	paypal	13%
33	facebook	1%	72	tumblr	15%
34	ign	1%	73	wikipedia	15%
35	internetarchive	1%	74	wordpress	28%
36	pinterest	1%	75	AskDotCom	39%
37	yahoonews	1%	76	bookingcom	44%
38	abcnews	2%	77	twitter	46%
39	bbcnews	2%	78	guardian	47%

TABLE 1. Behavioral profile violations of news agency and corporate Twitter accounts within most recent 100 tweets.

Alexa’s top 500 global sites. While a more exhaustive list would be beneficial, identifying a social network account that corresponds to a website is a manual process and thus does not scale well. Table 1 presents the list of the resulting 78 Twitter accounts after removal of duplicate entries cross listed in multiple categories.

For each account in this list COMPA then built the behavioral profile and compared the most recent 100 messages against the extracted profile. As for any detection system, COMPA needs to make tradeoffs between false positives and false negatives. To tune our system, we used as ground truth the 4 high-profile incidents described in Section 2. We configured COMPA to detect such attacks. We then analyzed the false positive rate that COMPA generates by using this threshold. Note that since these incidents are the only ones that have been reported for the involved accounts, this experiment resulted in no false negatives.

Table 1 also shows how many of these 100 messages violated their behavioral profile. The results indicate that the majority of popular accounts have little variability in their behavior. As we can see, the majority of the high profile accounts that we evaluated have a very consistent behavior.

In fact, as we will show in the next section, such accounts show a considerably more consistent behavior than average social network accounts. In these cases COMPA could protect these accounts and still reliably detect compromises without fearing false positives.

A handful of high profile accounts, however, showed a very variable behavior. In the worst case, the behavior of The Guardian’s Twitter account was so inconsistent that 47 out of 100 messages would have been flagged by COMPA as malicious. We suspect that these accounts are not used by a single person, but instead are managed by a set of different actors who have different preferences in terms of Twitter clients and slightly different editing styles. Our system is currently not able to characterize accounts with such multi-actor behavior patterns. In the general case of a single user operating a given account, however, COMPA can reliably detect and block changes of behavior.

5.2 Regular Accounts

To assess the consistency of behavioral profiles for regular accounts, we used COMPA to create 64,368 behavioral profiles for randomly selected Twitter users over a period of 44 days. We used the same threshold selected in Section 5.1 for this experiment. To this end, every minute, COMPA retrieved the latest tweet received from the Twitter stream and built a behavioral profile for the corresponding account. 2,606 (or 4%) of these messages violated their account’s behavioral profile. As we would not expect random messages to violate the behavioral profile of the underlying account, we consider these 4% the base false discovery rate of COMPA. Unfortunately, a 4% false discovery rate is exceedingly high for a practical deployment of a detection system such as COMPA. Thus, when dealing with regular accounts, instead of detecting compromises of individual user accounts, COMPA first groups accounts by means of message similarity into large-scale *campaigns*. COMPA declares members of a campaign as compromised only if a significant fraction of messages within that campaign violate their respective behavioral profiles.

Detecting Large-scale Social Network Compromises A single message that violates the behavioral profile of a user does not necessarily indicate that this user is compromised and the message is malicious. The message might merely reflect a normal change of behavior. For example, a user might be experimenting with new client software or expanding her topics of interest. Therefore, before we flag an account as compromised, we require that we can find a number of similar messages (within a specific time interval) that also violate the accounts of their respective senders.

Hence, we use message similarity as a second component to distinguish malicious messages from spurious profile violations. This is based on the assumption that attackers aim to spread their malicious messages to a larger victim population. In the following section, we discuss how our system groups together similar messages and assesses their maliciousness.

6 Detecting Large-scale Social Network Compromises

6.1 Grouping Messages

To perform this grouping of messages, we can either first group similar messages and then check all clustered messages for behavioral profile violations, or we can first analyze all messages on the social network for profile violations and then cluster only those that have resulted in violations. The latter approach offers more flexibility for grouping messages, since we only need to examine the small(er) set of messages that were found to violate their user profiles. This would allow us to check if a group of suspicious messages was sent by users that are all directly connected in the social graph, or whether these messages were sent by people of a certain demographics. Unfortunately, this approach requires to check *all* messages for profile violations. While this is certainly feasible for the social networking provider, our access to these sites is rate-limited in practice. Hence, we need to follow the first approach: More precisely, we first group similar messages. Then, we analyze the messages in clusters for profile violations. To group messages, we use the two simple similarity measures, discussed in the following paragraphs.

Content similarity. Messages that contain similar text can be considered related and grouped together. To this end, our first similarity measure uses n-gram analysis of a message’s text to cluster messages with similar contents. We use entire words as the basis for the n-gram analysis. Based on initial tests to evaluate the necessary computational resources and the quality of the results, we decided to use four-grams. That is, two messages are considered similar if they share at least one four-gram of words (i.e., four consecutive, identical words).

URL similarity. This similarity measure considers two messages to be similar if they both contain at least one link to a similar URL. The naïve approach for this similarity measure would be to consider two messages similar if they contain an identical URL. However, especially for spam campaigns, it is common to include identifiers into the query string of a URL (i.e., the part in a URL after the question mark). Therefore, this similarity measure discards the query string and relies on the remaining components of a URL to assess the similarity of messages. Of course, by discarding the query string, the similarity measure might be incorrectly considering messages as similar if the target site makes use of the query string to identify different content. Since YouTube and Facebook use the query string to address individual content, this similarity measure discards URLs that link to these two sites.

Many users on social networking sites use URL shortening services while adding links to their messages. In principle, different short URLs could point to the same page, therefore, it would make sense to expand such URLs, and perform the grouping based on the expanded URLs. Unfortunately, for performance reasons, we could not expand short URLs in our experiments. On Twitter, we observe several million URLs

per day (most of which are shortened). This exceeds by far the request limits imposed by any URL shortening service.

We do not claim that our two similarity measures represent the only ways in which messages can be grouped. However, as the evaluation in Section 7 shows, the similarity measures we chose perform very well in practice. Furthermore, our system can be easily extended with additional similarity measures if necessary.

6.2 Compromised Account Detection

Our approach groups together similar messages that are generated in a certain time interval. We call this the *observation interval*. For each group, our system checks all accounts to determine whether each message violates the corresponding account’s behavioral profile. Based on this analysis, our approach has to make a final decision about whether an account is compromised or not.

Suspicious groups. A group of similar messages is called a *suspicious group* if the fraction of messages that violates their respective accounts’ behavioral profiles exceeds a threshold th . In our implementation, we decided to use a threshold that is dependent on the size of the group. The rationale behind this is that, for small groups, there might not be enough evidence of a campaign being carried out unless a high number of similar messages violate their underlying behavioral profiles. In other words, small groups of similar messages could appear coincidentally, which might lead to false positives if the threshold for small groups is too low. This is less of a concern for large groups that share a similar message. In fact, even the existence of large groups is already somewhat unusual. This can be taken into consideration by choosing a lower threshold value for larger groups. Accordingly, for large groups, it should be sufficient to raise an alert if a smaller percentage of messages violate their behavioral profiles. Thus, the threshold th is a linear function of the size of the group n defined as $th(n) = \max(0.1, kn + d)$.

Based on small-scale experiments, we empirically determined that the parameters $k = -0.005$ and $d = 0.82$ work well. The *max* expression assures that at least ten percent of the messages in big groups must violate their behavioral profiles to get the group’s users flagged as compromised. Our experiments show that these threshold values are robust, as small modifications do not influence the quality of the results. Whenever there are more than th messages in a group (where each message violates its profile), COMPA declares all users in the group as compromised.

Bulk applications. Certain popular applications, such as Nike+ or Foursquare, use templates to send similar messages to their users. Unfortunately, this can lead to false positives. We call these applications bulk applications. To identify popular bulk applications that send very similar messages in large amounts, COMPA needs to distinguish regular client applications (which do not automatically post using templates) from bulk applications. To this end, our system analyzes a randomly selected set of S messages for each application,

drawn from *all* messages sent by this application. COMPA then calculates the average pairwise Levenshtein ratios for these messages. The Levenshtein ratio is a measure of the similarity between two strings based on the edit distance. The values range between 0 for unrelated strings and 1 for identical strings. We empirically determined that the value 0.35 effectively separates regular client applications from bulk applications.

COMPA flags all suspicious groups produced by client applications as compromised. For bulk applications, a further distinction is necessary, since we only want to discard groups that are due to *popular* bulk applications. Popular bulk applications constantly recruit new users. Also, these messages are commonly synthetic, and they often violate the behavioral profiles of new users. For existing users, on the other hand, past messages from such applications contribute to their behavioral profiles, and thus, additional messages do not indicate a change in behavior. If many users made use of the application in the past, and the messages the application sent were in line with these users’ behavioral profiles, COMPA considers such an application as popular.

To assess an application’s popularity, COMPA calculates the number of distinct accounts in the social network that made use of that application before it has sent the first message that violates a user’s behavioral profile. This number is multiplied by an age factor (which is the number of seconds between the first message of the application as observed by COMPA and the first message that violated its user’s behavioral profile). The intuition behind this heuristic is the following: An application that has been used by many users for a long time should not raise suspicion when a new user starts using it, even if it posts content that differs from this user’s established behavior. Manual analysis indicated that bulk applications that are used to run spam and phishing campaigns over compromised accounts have a very low popularity score. Thus, COMPA considers a bulk application to be popular if its score is above 1 million. We assume that popular bulk applications do not pose a threat to their users. Consequently, COMPA flags a suspicious group as containing compromised accounts only if the group’s predominant application is a non-popular bulk application.

7 Evaluation

We implemented our approach in a tool, called COMPA and evaluated it on Twitter and Facebook; we collected tweets in real time from Twitter, while we ran our Facebook experiments on a large dataset crawled in 2009.

We show that our system is capable of building meaningful behavioral profiles for individual accounts on both networks. By comparing new messages against these profiles, it is possible to detect messages that represent a (possibly malicious) change in the behavior of the account. By grouping together accounts that contain similar messages, many of which violate their corresponding accounts’ behavioral profiles, COMPA is

able to identify groups of compromised accounts that are used to distribute malicious messages on these social networks. Additionally, COMPA identifies account compromises without a subsequent grouping step if the underlying behavioral profile is consistent over time. We continuously ran COMPA on a stream of 10% of all public Twitter messages on a single computer (Intel Xeon X3450, 16 GB ram). The main limitation was the number of user timelines we could request from Twitter, due to the enforced rate-limits. Thus, we are confident that COMPA can be scaled up to support online social networks of the size of Twitter with moderate hardware requirements.

We first detail the dataset we used to perform the evaluation of our work. Subsequently, we discuss a series of real world account compromises against popular Twitter accounts that COMPA could have prevented, and conclude this section with an evaluation of large-scale compromises that COMPA detected on the Twitter and Facebook social networks.

7.1 Data Collection

Twitter Dataset We obtained elevated access to Twitter’s streaming and RESTful API services. This allowed us to collect around 10% of all public tweets through the streaming API, resulting in roughly 15 million tweets per day on average. We collected this data continuously starting May 13, 2011 until Aug 12, 2011. In total, we collected over 1.4 billion tweets from Twitter’s stream. The stream contains live tweets as they are sent to Twitter. We used an observation interval of one hour. Note that since the stream contains randomly sampled messages, COMPA regenerated the behavioral profiles for all involved users every hour. This was necessary, because due to the 10% random sampling it was not guaranteed that we would see the same user multiple times.

To access the historical timeline data for individual accounts, we rely on the RESTful API services Twitter provides. To this end, Twitter whitelisted one of our IP addresses, which allowed us to make up to 20,000 RESTful API calls per hour. A single API call results in at most 200 tweets. Thus, to retrieve complete timelines that exceed 200 tweets, multiple API requests are needed. Furthermore, Twitter only provides access to the most recent 3,200 tweets in any user’s timeline. To prevent wasting API calls on long timelines, we retrieved timeline data for either the most recent three days, or the user’s 400 most recent tweets, whatever resulted in more tweets.

On average, we received tweets from more than 500,000 distinct users per hour. Unfortunately, because of the API request limit, we were not able to generate profiles for all users that we saw in the data stream. Thus, as discussed in the previous section, we first cluster messages into groups that are similar. Then, starting from the largest cluster, we start to check whether the messages violate the behavioral profiles of their senders. We do this, for increasingly smaller clusters, until our API limit is exhausted. On average, the created groups consisted of 30 messages. This process is then repeated for the next observation period.

Facebook Dataset Facebook does not provide a convenient

way of collecting data. Therefore, we used a dataset that was crawled in 2009. We obtained this dataset from an independent research group that performed the crawling in accordance with the privacy guidelines at their research institution. Unfortunately, Facebook is actively preventing researchers from collecting newer datasets from their platform by various means, including the threat of legal action. This dataset was crawled from geographic networks on Facebook. Geographic networks were used to group together people that lived in the same area. The default privacy policy for these networks was to allow anybody in the network to see all the posts from all other members. Therefore, it was easy, at the time, to collect millions of messages by creating a small number of profiles and join one of these geographic networks. For privacy reasons, geographic networks have been discontinued in late 2009. The dataset we used contains 106,373,952 wall posts collected from five geographic networks (i.e., London, New York, Los Angeles, Monterey Bay, and Santa Barbara). These wall posts are distributed over almost two years (Sept. 2007 - July 2009).

7.2 Detection on Twitter

The overall results for our Twitter evaluation are presented in Table 2. Due to space constraints, we will only discuss the details for the *text similarity measure* here. However, we found considerable overlap in many of the groups produced by both similarity measures. More precisely, for over 8,200 groups, the two similarity measures (content and URL similarity) produced overlaps of at least eight messages. COMPA found, for example, phishing campaigns that use the same URLs and the same text in their malicious messages. Therefore, both similarity measures produced overlapping groups.

The *text similarity* measure created 374,920 groups with messages of similar content. 365,558 groups were reported as legitimate, while 9,362 groups were reported as compromised. These 9,362 groups correspond to 343,229 compromised accounts. Interestingly, only 12,238 of 302,513 applications ever produced tweets that got grouped together. Furthermore, only 257 of these applications contributed to the groups that were identified as compromised.

For each group of similar messages, COMPA assessed whether the predominant application in this group was a regular client or a bulk application. Our system identified 12,347 groups in the bulk category, of which 1,647 were flagged as compromised. Moreover, COMPA identified a total of 362,573 groups that originated from client applications. Of these, 7,715 were flagged as compromised.

Overall, our system created a total of 7,250,228 behavioral profiles. COMPA identified 966,306 messages that violate the behavioral profiles of their corresponding accounts. Finally, 400,389 messages were deleted by the time our system tried to compare these messages to their respective behavioral profiles (i.e., within an hour).

Network & Similarity Measure	Twitter Text		Twitter URL		Facebook Text	
	Groups	Accounts	Groups	Accounts	Groups	Accounts
Total Number	374,920		14,548		48,586	
# Compromised	9,362	343,229	1,236	54,907	671	11,499
False Positives	4% (377)	3.6% (12,382)	5.8% (72)	3.8% (2,141)	3.3% (22)	3.6% (412)
# Bulk Applications	12,347		1,569		N/A	N/A
# Compromised Bulk Applications	1,647	178,557	251	8,254	N/A	N/A
False Positives	8.9% (146)	2.7% (4,854)	14.7% (37)	13.3% (1,101)	N/A	N/A
# Client Applications	362,573		12,979		N/A	N/A
# Compromised Client Applications	7,715	164,672	985	46,653	N/A	N/A
False Positives	3.0% (231)	4.6% (7,528)	3.5% (35)	2.2% (1,040)	N/A	N/A

TABLE 2. Evaluation Results for the Text (Twitter and Facebook) and URL (Twitter) Similarity measure.

False Positives Using the text similarity measure, COMPA identified 343,229 compromised Twitter accounts in 9,362 clusters. We performed an exhaustive false positive analysis of COMPA in our previous work [15]. Due to space limitations, we omit repeating this description here. In summary, 377 of the 9,362 groups (4%) that COMPA flagged as containing compromised are labeled as false positives. Note that each group consists of multiple tweets, each from a different Twitter account. Thus, the above mentioned results are equivalent to flagging 343,229 user as compromised, where 12,382 (3.6%) are false positives.

One characteristic that directly affects the probability of a false positive detection is the length of the message stream that is used to learn the behavioral profile. Intuitively, the longer a user’s messages stream is, the more comprehensive is the resulting behavioral profile. For a detailed discussion and analysis of this intuition, we again refer to [15].

False Negatives Precisely assessing false negatives in large datasets, such as the ones we are evaluating COMPA on, is a challenging endeavor. However, we found after extensive sampling (64,000 random accounts) that the grouping feature in COMPA did not cause undue amounts of false negatives. In our previous work we detail our analysis to conclude that COMPA suffers from roughly 4% false negatives in detecting compromised accounts of regular Twitter users.

7.3 Detection on Facebook

As the Facebook dataset spans almost two years we increased the *observation interval* to eight hours to cover this long timespan. Furthermore, we only evaluated the Facebook dataset with the text similarity measure to group similar messages.

Our experiments indicated that a small number of popular applications resulted in a large number of false positives. Therefore, we removed the six most popular applications, including *Mafia Wars* from our dataset. Note that these six applications resulted in groups spread over the whole dataset. Thus, we think it is appropriate for a social network administrator to white-list applications at a rate of roughly three instances per year.

In total, COMPA generated 206,876 profiles in 48,586 groups and flagged 671 groups as compromised (i.e., 11,499 compromised accounts). All flagged groups are created by

bulk applications. 22 legitimate groups were incorrectly classified (i.e., 3.3% false positives) as compromised; they contained 412 (3.6%) users.

7.4 Case studies

As mentioned in Section 5.1, COMPA successfully detected four high-profile Twitter compromises. In the following, we discuss those incidents in more detail, highlighting what type of anomalies were picked up by COMPA compared to the typical behavior of these accounts. In addition, we discuss a compromise that was simulated by the fast-food company Chipotle on their Twitter account, for promotional reasons. We demonstrate that in this case the message did not show particular anomalies compared to the typical behavior of the account, and therefore COMPA would have correctly detected it as being authored by their legitimate owners.

Associated Press. Comparing the malicious message message against the behavioral profile of the @AP account resulted in significant differences among many features that our system evaluates. For example, the fake news was posted via the Twitter website, whereas the legitimate owners of the @AP account commonly use the SocialFlow application to send status updates. Furthermore, the fake tweet did not include any links to additional information, a practice that the @AP account follows very consistently.

Only two features in our behavioral model did not signify a change of behavior. The time when the tweet was sent (i.e., 10:07UTC) and the language of the tweet itself. The authors of the @AP account as well as the attackers used the English language to author their content. While the language is undoubtedly the same, a more precise language analysis could have determined an error in capitalization in the attacker’s message.

FoxNews Politics. This tweet violated almost all the features used by our system. For example, the tweet was sent in the middle of the night (i.e., 23:24UTC), through the main Twitter web site. Furthermore, it did not include a link to the full story on the Fox News website. The tweet also made extensive use of hashtags and mentions, a practice not commonly used by the @foxnewspolitics account.

Skype. COMPA successfully detected the compromise because the offending message significantly diverged from the

behavioral profile constructed for the Skype account. The only two features that did not diverge from the behavioral profile were the time and language information. Since the Skype profile as well as the malicious message were authored in English, COMPA did not detect a deviation in this feature. More interestingly, however, the time the message was sent, perfectly aligned with the normal activity of the Skype account. We would assume that an observant legitimate owner of the account would detect such a malicious message during their regular activity. However, presumably because of the holiday season, it took more than two hours before the offending message was removed by the legitimate owners of the Skype account. In the meantime, the offending message got retweeted over 8,000 times. This incident prominently demonstrates the advantages an automated technique for the detection of compromised accounts would entail, as such attacks can have significant negative impact on a brand's online reputation.

Yahoo! News. Our system detected significant deviations of the offending message when compared to the extracted behavioral profile for the account. Similarly to the above mentioned cases, the attackers used Twitter's web portal to send the offending messages, whereas YahooNews predominantly relies on the TweetDeck application to post new content. While YahooNews frequently links to detailed information and often mentions their source by using the direct communication feature (i.e., @-mentions), the offending tweets featured neither of these characteristics.

Chipotle. On July 21, 2013 multiple news websites reported that the main Twitter account of the Chipotle Mexican Grill restaurant chain got compromised¹. Indeed, twelve "unusual" successive messages were posted to the @chipotletweets account that day, before the apparent legitimate operator acknowledged that they experienced issues with their account. Because this was in the midst of other compromises of high-profile accounts (e.g., Jeep, Burger King, and Donald Trump), this alert seemed credible. However, when we ran COMPA on these twelve messages in question, only minor differences to the behavioral profile of the Chipotle account emerged. More precisely, the offending messages did not contain any direct user interaction (i.e., mentions) – a feature prominently used by the legitimate operator of that account. However, because this was the only difference compared to the learned behavioral profile, COMPA's classifier did not consider the deviation significant enough to raise a warning about an account compromise. Interestingly, three days later, Chipotle acknowledged that they had faked the account compromise as a publicity measure [23]. This illustrates that even trying to fake an account compromise is a non-trivial endeavor. As mentioned, all other features besides the direct user interaction were perfectly in line with the behavioral profile. When we investigated the application source model for the Chipotle account we learned that it is almost exclusively managed via

1. At the time of writing, the public timeline of the @chipotletweets account still contains these tweets.

the SocialEngage client application. Thus, for an attacker to stealthily compromise Chipotle's account, he would also have to compromise Chipotle's SocialEngage account. A similar attempt of faking an account compromise staged by MTV [24] did also not result in COMPA raising an alert. Because of our limited view of Twitter's traffic (i.e., we only see a random 10% sample), we could not evaluate the faked compromise of the BET account staged in the same campaign by the same actors.

8 Limitations

An attacker who is aware of COMPA has several possibilities to prevent his compromised accounts from being detected by COMPA. First, the attacker can post messages that align with the behavioral profiles of the compromised accounts. As described in Section 4, this would require the attacker to invest significant time and computational resources to gather the necessary profile information from his victims. Furthermore, social networks have mechanisms in place that prevent automated crawling, thus slowing down such data gathering endeavors.

In the case of COMPA protecting regular accounts an attacker could send messages that evade our similarity measures, and thus, although such messages might violate their compromised accounts' behavioral profiles, they would not get grouped together. To counter such evasion attempts, COMPA can be easily extended with additional and more comprehensive similarity measures. For example, it would be straight-forward to create a similarity measure that uses the landing page instead of the URLs contained in the messages to find groups of similar messages. Furthermore, more computationally expensive similarity measures, such as text shingling or edit distances for text similarity can also be implemented. Other similarity measures might leverage the way in which messages propagate along the social graph to evaluate message similarity.

9 Related Work

The popularity of social networks inspired many scientific studies in both, networking and security. Wilson et al. ran a large-scale study of Facebook users [25], while Krishnamurthy et al. provide a characterization of Twitter users [26]. Kwak et al. analyze the differences between Twitter and the more traditional social networks [27].

Yardi et al. [28] ran an experiment on the propagation of spam on Twitter. Their goal was to study how spammers use popular topics in their messages to reach more victims. To do this, they created a hashtag and made it trending, and observed that spammers started using the hashtag in their messages.

Early detection systems for malicious activity on social networks focused on identifying fake accounts and spam messages [8], [9], [10] by leveraging features that are geared towards recognizing characteristics of spam accounts (e.g., the presence of URLs in messages or message similarity in user

posts). Cai et al. [29] proposed a system that detects fake profiles on social networks by examining densely interconnected groups of profiles. These techniques work reasonably well, and both Twitter and Facebook rely on similar heuristics to detect fake accounts [30], [31].

In response to defense efforts by social network providers, the focus of the attackers has shifted, and a majority of the accounts carrying out malicious activities were not created for this purpose, but started as legitimate accounts that were compromised [12], [2]. Since these accounts do not show a consistent behavior, previous systems will fail to recognize them as malicious. Grier et al. [2] studied the behavior of compromised accounts on Twitter by entering the credentials of an account they controlled on a phishing campaign site. This approach does not scale as it requires identifying and joining each new phishing campaign. Also, this approach is limited to phishing campaigns. Gao et al. [12] developed a clustering approach to detect spam wall posts on Facebook. They also attempted to determine whether an account that sent a spam post was compromised. To this end, the authors look at the wall post history of spam accounts. However, the classification is very simple. When an account received a benign wall post from one of their connections (friends), they automatically considered that account as being legitimate but compromised. The problem with this technique is that previous work showed that spam victims occasionally send messages to these spam accounts [10]. This would cause their approach to detect legitimate accounts as compromised. Moreover, the system needs to know whether an account has sent spam before it can classify it as fake or compromised. Our system, on the other hand, detects compromised accounts also when they are not involved in spam campaigns. As an improvement to these techniques, Gao et al. [11] proposed a system that groups similar messages posted on social networks together, and makes a decision about the maliciousness of the messages based on features of the message cluster. Although this system can detect compromised accounts, as well as fake ones, their approach is focused on detecting accounts that spread URLs through their messages, and, therefore, is not as generic as COMPA.

Thomas et al. [14] built Monarch to detect malicious messages on social networks based on URLs that link to malicious sites. By relying only on URLs, Monarch misses other types of malicious messages. For example, our previous work [15] illustrates that COMPA detects scams based on phone numbers and XSS worms spreading without linking to a malicious URL.

WARNINGBIRD [13] is a system that detects spam links posted on Twitter by analyzing the characteristics of HTTP redirection chains that lead to a final spam page.

Xu et al. [32] present a system that, by monitoring a small number of nodes, detects worms propagating on social networks. This paper does not directly address the problem of compromised accounts, but could detect large-scale infections such as *koobface* [33]. Chu et al. [34] analyze three cate-

gories of Twitter users: humans, bots, and cyborgs, which are software-aided humans that share characteristics from both bots and humans. To this end, the authors use a classifier that examines how regularly an account tweets, as well as other account features such as the application that is used to post updates. Using this paper's terminology, compromised accounts would fall in the cyborg category. However, the paper does not provide a way of reliably detecting them, since these accounts are often times misclassified as either bots or humans. More precisely, their true positive ratio for *cyborg* accounts is only of 82.8%. In this paper, we showed that we can detect such accounts much more reliably. Also, the authors in [34] do not provide a clear distinction between compromised accounts and legitimate ones that use third-party applications to post updates on Twitter.

Yang et al. [35] studied new Twitter spammers that act in a stealthy way to avoid detection. In their system, they use advanced features such as the topology of the network that surrounds the spammer. They do not try to distinguish compromised from spam accounts.

Recent work in the online abuse area focused on detecting accounts that are accessed by botnets, by either looking at accounts that are accessed by many IP addresses [36] or by looking at accounts that present strong synchronized activity [37]. COMPA can detect compromised accounts that are accessed by botnets as well, but has the additional advantage of being able to identify and block hijacked accounts that are used in isolation.

10 Conclusions

In this paper, we presented COMPA, a system to detect compromised accounts on social networks. COMPA uses statistical models to characterize the behavior of social network users, and leverages anomaly detection techniques to identify sudden changes in their behavior. The results show that our approach can reliably detect compromises affecting high-profile social network accounts, and can detect compromises of regular accounts, whose behavior is typically more variable, by aggregating together similar malicious messages.

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