Spammers Are Becoming “Smarter” on Twitter

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witter has become one of the most commonly used communication tools in daily life. With 500 million users, Twitter now generates more than 500 million tweets per day. However, its popularity has also attracted spamming. Spammers spread many intensive tweets, which can lure legitimate users to commercial or malicious sites containing malware downloads, phishing, drug sales, scams, and more.

Spammers are becoming more cunning on Twitter. While researchers are developing methods to detect spammers continuously, spammers continuously invent new strategies to bypass detection. Here, we review the well-known methods that spammers have used to avoid or reduce their chances of being caught on Twitter. We show that spammers are now using more advanced strategies, namely coordinated posting behavior, finite-state-machine-based spam template, and passive spam.

Well-Known Spamming Strategies
At the most basic level, spammers use various Twitter functions such as @ and hashtags (#) to engage victims. Although researchers, as well as Twitter itself, have attempted to combat spam, the percentage of spam in the whole platform is still high. We hypothesize that this is because spammers are becoming more cunning on Twitter.

To bypass such detection systems, spammers apply evasion tactics, such as gaining more followers, posting more tweets, and so on. They aren’t exposed by the...
simple detection systems already described because their activity mimics that of legitimate users. To combat this, researchers propose robust social graph-based features, such as local clustering coefficients, betweenness centrality, and distance/connectivity to detect those tweets fabricated by spammers.

In addition to the aforementioned spamming strategies, our Twitter spam analysis reveals that spammers are now using more advanced methods.

**Coordinated Posting Behavior**

We collected a dataset of more than 570 million tweets with URLs from 25 September 2013 to 9 October 2013. Within this dataset, we identified around 33 million spam tweets using Trend Micro’s Web Reputation Technology; this accounts for 5.8 percent of the total tweets. We then used bipartite cliques to cluster the spam tweets into 17 groups, as shown in Table 1 (see the “Bipartite Cliques” sidebar for details about this method). Seventeen groups dominate more than 75 percent of the spam, whereas “others” account for less than 25 percent, indicating that, in general, spam is sent by groups.

We also found that six groups in Table 1 (groups A, B, C, E, I, and J, the bold, italicized letters in the table) had some common features:

- The URLs embedded in the tweets tend to use a .ru (server of Russian origin) domain.
- The content of the landing pages were written in Russian.
- The URLs tended to end with a Unix timestamp, such as http://xxxx.ru/xxxx-1380642617.html.

To study the spamming behavior of these six groups, we counted the tweets sent per hour by each group. Group A spread spam actively from 26 September (see Figure 1). When

<table>
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<th>Table 1. Spam breakdown.</th>
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<td><strong>Group</strong></td>
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<td>P</td>
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<tr>
<td>Q</td>
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<tr>
<td>Other spam</td>
</tr>
</tbody>
</table>

We named spam types according to the spam’s content—for example, craked software spam is about cracked software.

**Twitter Features**

The following Twitter features were relevant to our work:

- **Mention (@):** If a tweet contains the @user tag, it is called a mention. The mentioned tweet can appear in a user’s timeline even if the sender is neither followed by nor follows the user.
- **Hashtag (#):** A hashtag embedded in a tweet is normally a keyword to describe this tweet. If the hashtagged keyword is very popular, it will become a trending topic that can be seen by all Twitter users.
- **Timeline:** The tweets sent by those a user follows or tweets that use @ to mention the user appear in the user’s timeline.

**Bipartite Clique**

To identify the bipartite cliques, we first extracted the domains of URLs embedded in tweets along with those tweets’ senders. Then, we constructed a graph in which the Twitter users were nodes on one side of the graph while the domains in sent tweets were nodes on the other side. For each tweet from user $U$ that contained a link with domain $D$, we connected this user $U$ to domain $D$ in the graph. Once the graph was fully connected, a bipartite clique was formed.
group A stopped sending spam, group C started sending it on 4 October. Groups C and E, and E and J also displayed this type of spamming behavior. We regard this behavior as coordinated posting behavior, a phenomenon in which one group of spam tweets disappears while another is being sent. This kind of posting behavior is more difficult to detect because spammers change the groups of accounts to abuse Twitter.

**Finite-State Machine-Based Spam Template**

Some have found that most spam is generated using specific templates, which is logical because it is very expensive for spammers to write each tweet manually. However, the template is often simple—for example, “celebrity name” + “an eye-catching action” + URL. Therefore, researchers can extract the templates and match tweets to them to detect spam.

We found that spammers are now using more complex templates to generate spam. Surprisingly, spammers are using finite-state machines to generate what we have named finite-state machine-based spam templates (see Figure 2). One finite-state machine has a number of states, and each edge of it is denoted by one word. If we travel from the beginning to the end, we can have one full sentence, such as “lol, this tweet by you is funny + SHORT_URL” in the finite-state machine. By using one finite-state machine-based spam template, spammers can generate many different tweets. Take the finite-state machine in Figure 2, for example; it has $8 \times 5 \times 3 \times 2 \times 9 = 2,160$ different routes from start to end. This means that spammers can use this template to generate 2,160 different spam tweets with little effort. For example, spammers can write a script that randomly chooses one option from each node to generate one spam tweet. Relying on simple string signatures to match spam tweets will allow most of these finite-state machine-based template spam tweets to escape detection.

**Passive Spam**

As previously described, traditional spam is distributed using Twitter functions such @ and #. However, we also found that much spam...
does not use any tags. As a result, such spam cannot be identified by machine-learning-based spam detection that uses these features. Contrary to traditional spam, which tries to involve victims as much as possible, this spam is only viewed by victims when they search for specific key words. Consequently, we call this passive spam. None of these spam tweets have tags embedded (see Figure 3), and they are mostly promoting cracked games, software, or pirated movies.

We found that of the victims who clicked on this kind of spam, 90 percent were in Russia. However, victims from many non-Russian-speaking countries also clicked on this kind of spam. Assuming these users did not speak Russian, we hypothesize that the content advertised in this spam was sufficiently enticing for victims to use translation software to access the inappropriate content. We also found that the suspended rate of this type of spam by Twitter is much lower than others, because spammers have much less interaction with users, allowing spammers to use this strategy successfully.

Although researchers and industry are devoted to developing detection and mitigation approaches to combat Twitter spam, spammers can thwart their efforts with ever-evolving techniques, such as the three complex spamming strategies we describe here. The war with spammers is becoming fiercer and is far from over; we should therefore continue to analyze spammers’ behavior and propose robust spam-detection systems to make a safe Twitter environment for all users.

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References
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