Spying on Spammers:
Tracking Like Farm Accounts on Facebook

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\textbf{ABSTRACT}

The increasing reliance on online social networks for user engagement motivates the need to understand and counter reputation manipulation activities, such as boosting the number of Facebook page Likes. This paper presents an in-depth analysis of Facebook accounts used by a few Like Farms. We crawl their timelines and compare their activities to a baseline sample of normal users. Then, we retrieve the pages they like and cluster their activity. We find that, compared to normal users, posts from Like Farm accounts often consist of re-shared content, have fewer words and poor vocabulary, are targeted to a limited number of topics and generate more comments and Likes. Profiles used by Like Farms are also more likely to be tagged or tag their friends, and their Likes are concentrated around specific pages. While we highlight the challenges faced by currently deployed anti-fraud tools in detecting stealthy Like Farm campaigns and networks, our analysis provides important insights that can be incorporated into detection algorithms.

1. INTRODUCTION

Online social networks enable organizations and individuals to reach out to large audiences, offering a number of tools to engage with worldwide users while requiring minimal costs and infrastructure. Among these, Facebook pages\textsuperscript{1} are an important asset for companies, businesses, and public figures, as they can be used to broadcast updates, promote products/events, or engage with customers and fans. The number of Likes of a Facebook page is often considered a measure of its popularity and profitability [7]. Facebook allows page owners to promote their pages via targeted ad campaigns. At the same time, a number of “Like Farms” also offer services that artificially inflate the number of Likes on a given page, relying on fake and compromised accounts, workers, and collusion networks [20].

In this paper, we set to analyze online public profiles of accounts used by Like Farms that engage in reputation manipulation. We characterize the extent to which content on these profiles is different from regular, randomly chosen public profiles, which can be used to distinguish between legitimate and misbehaving reputation-building activities, and ultimately detect malicious accounts.

\textbf{Problem Statement.} Our prior work [9] suggests that Like Farms follow two main modi operandi. In a honeypot-based measurement study (conducted in Spring 2014), we found that a first category of farms seem to follow a \textit{na"ive} approach: they do not try to hide their activities, but rely on a large number of accounts (possibly fake or compromised) instructed to like target pages within a short timespan. A second category of farms, instead, follow a \textit{stealthier} approach, instrumenting possibly human-operated profiles to gradually spread Likes, over longer timespans.

Arguably, one would expect fraud detection algorithms to detect \textit{na"ive} Like Farms more effectively than the \textit{stealthier} ones. Tools like CopyCatch [2] and SynchroTrap [6], which are currently deployed by Facebook, are indeed geared to detect bursty Like patterns. To test this hypothesis, in [9], we checked whether accounts of Likers attracted by honey-pots were still active a month after the campaigns had finished: Facebook did not terminate most of the accounts (e.g., the “stealthiest” farm had only 1/621 accounts terminated), highlighting the difficulty of detecting stealthy behavior.

This motivates the need to analyze the \textit{collective and individual} behavior of accounts operated by Like Farms. In this paper, we focus on (i) quantifying collective actions (i.e., Like campaigns) by Like Farm accounts for their customers, and (ii) studying manipulation tactics employed by individual Like Farm accounts to look normal and avoid detection. For the former, our goal is to design methods to generate campaign signatures to accurately identify and cluster future campaigns by stealthy Like Farms upon their onset. For the latter, we aim to detect reputation manipulation techniques used by accounts belonging to stealthy farms.

\textbf{Roadmap.} First, we present an in-depth analysis of Like Farm accounts. We crawl their timelines, collecting information about status updates, pictures, and comments, and compare them to a baseline sample of normal users. We posit that, to make accounts look like they behave like regular users, Like Farm operators might be using a “catfish” approach, i.e., replicating activities of other known users, copying posts and pictures from other accounts, or pasting content from search engines, Wikipedia, etc, and some

\textsuperscript{1}Authors contributed equally.
\textsuperscript{2}https://www.facebook.com/about/pages
may also recruit real users using online marketplaces, such as SEOClerks.com and Fiverr.com. Second, with the ultimate goal of identifying Like Farm campaigns (i.e., groups of pages liked by Like Farm users), we retrieve the list of pages liked by Like Farm accounts, and study their behavior by clustering their activity in our crawls. We further analyze the main properties of pages grouped into different clusters, including their Like count, categories, and locations.

**Summary of findings.** Compared to baseline users, Like Farm users exhibit a few distinct characteristics. Our lexical analysis of timelines reveals that Like Farm users’ posts have 43% fewer words, a poorer vocabulary, and lower readability. Moreover, their posts are highly targeted to some specific topics, generate more comments and Likes, and a significant fraction of their posts consist of “shared activity” (i.e., sharing posts made by other users, articles, videos, and external URLs). Furthermore, these users are more likely to be tagged or tag their friends on their timeline activity than baseline users. We also notice that Like Farm users’ liking activities are concentrated around specific target pages and exhibit a chameleon effect by liking popular pages.

## 2. DATASETS

We now present the datasets used in the rest of the paper.

### Campaigns

In Spring 2014 [9], we conducted a measurement analysis of Facebook Like fraud, relying on 13 honeypot Facebook pages called “Virtual Electricity,” which we intentionally kept empty (no posts or pictures). We promoted five pages using Facebook (FB) Ads, with each campaign targeting users, resp., in USA, France, India, Egypt, and worldwide. For the other eight pages, we used four popular Like Farms—BoostLikes.com (BL), SocialFormula.com (SF), AuthenticLikes.com (AL), and MammothSocials.com (MS)—employing them to deliver Likes targeting worldwide and USA users. In the rest of the paper, we refer to the campaigns with their acronyms followed by their target, e.g., SF-ALL denotes the SocialFormula campaign targeting worldwide users. Overall, we attracted Likes from a total of 5,616 unique Facebook profiles (1,437 from Facebook Ads and 4,179 from the Like Farm campaigns) [9]. Note that BL-ALL and MS-ALL did not deliver any Likes, even though they were paid. We also analyze a sample of 1,408 random users previously collected by [8], which forms a baseline of normal accounts.

### Likes

In Spring 2014, we crawled, using Selenium webdriver [1], the list of pages liked by each of the 7,024 users (5,616 Facebook Ad/Like Farm users and 1,408 baseline users). After a year, in Spring 2015, we crawled again the list of pages liked by these users. We denote these two crawls, respectively, as old and new crawls. Using the page ID information in both crawls, we collected the information associated with each page, such as total number of Likes, category and location. Overall, we captured information from more than 1.1 million pages.

### Timelines

We also crawled the timeline information (aka Facebook wall) available for the 7,024 users, whenever this data was publicly available. In Spring 2015, we crawled timeline posts that were not older than 6 months (capping at a maximum of 500 posts), the latest comments on each post, as well as the associated number of Likes it received, and the number of comments (if hidden in the page rendering). In total, we collected more than 293K posts (messages, shared content, check-ins, etc.) from Facebook Ad/Like Farm users, and 35K posts from the baseline dataset.

### Inactive Accounts

Of the 5,616 accounts from the old crawl, we found that 642 (~11%) accounts were inactive at the time of the new crawl: 210 out of 1,437 from the Facebook Ad campaigns and 432 out of 4,179 from the Like Farm campaigns, yielding a total of 4,974 active accounts. Table 1 summarizes the accounts used for our measurements in the rest of the paper.

### Ethics Considerations

Although we only collected openly available data, we did collect (public) profile information, such as timeline information and page Likes. We could not request consent, but we enforced a few mechanisms to protect user privacy: all data was encrypted at rest and not redistributed, and no personal information was extracted as we only analyzed aggregated statistics.

## 3. ANALYSIS

In this section, we present a characterization analysis of users’ timelines and interactions with posts, then, we examine the liking behavior of Like Farm users by clustering their activity in both the old and new crawls.

### 3.1 Timelines

**Nature of Timeline Events.** We start our analysis by studying the timelines of the Facebook profiles in our datasets (cf. Section 2), collecting publicly available timeline information—posts, shared content, likes, and check-ins. Figure 1(a) shows, for the three user categories, the breakdown of timeline posts into images, videos, text, and others (e.g., links and posts from installed apps). Notably, a significant portion of posts consist of text (48–55%), followed by images (28–35%), and others (8–18%), but we did not observe any statistically significant difference across the user account categories.

**Word Count.** Figure 1(b) plots the distribution of posts’ average word counts across user categories: Like Farm ac-

### Table 1: Statistics for datasets and campaigns used in the paper.

<table>
<thead>
<tr>
<th>Campaign</th>
<th>#Users</th>
<th>#Pages Liked</th>
<th>#Posts</th>
</tr>
</thead>
<tbody>
<tr>
<td>FB-USA</td>
<td>5,616</td>
<td>732,738</td>
<td>30</td>
</tr>
<tr>
<td>BL-USA</td>
<td>483</td>
<td>35,909</td>
<td>35,087</td>
</tr>
<tr>
<td>SF-ALL</td>
<td>850</td>
<td>732,738</td>
<td>46,300</td>
</tr>
<tr>
<td>SF-USA</td>
<td>641</td>
<td>224,609</td>
<td>38,942</td>
</tr>
<tr>
<td>AL-ALL</td>
<td>695</td>
<td>484,127</td>
<td>61,519</td>
</tr>
<tr>
<td>AL-USA</td>
<td>821</td>
<td>312,420</td>
<td>30,689</td>
</tr>
<tr>
<td>MS-USA</td>
<td>287</td>
<td>390,033</td>
<td>12,272</td>
</tr>
<tr>
<td>Baseline</td>
<td>1,408</td>
<td>141,352</td>
<td>24,907</td>
</tr>
</tbody>
</table>
Aiming to assess the genuineness of Facebook Ads/Like Farm users, we characterize their interactions with posts according to different metrics, and compare them to those of baseline users. For Facebook Ads campaigns, we only focus on FB-IND, FB-EGY, and FB-ALL, since FB-FRA and FB-USA do not have enough users.

In Figure 3, we plot the distributions of the number of comments a post attracts. Specifically, Figure 3(a) shows that users from the Facebook Ads campaigns receive more comments on their posts compared to baseline and Like Farm users. A closer look at the individual campaigns, respectively, in Figures 3(b) and 3(c), reveals that users of all Facebook Ads campaigns and those of two Like Farm campaigns, i.e., BL-USA and AL-ALL, generate more comments than the baseline users. Since these two farms account for 46% of the timeline activity for all Like Farms, they contribute to the somewhat skewed distribution in Figure 3(a).

In Figure 4, we plot the number of Likes associated with users’ posts in the different campaigns, highlighting that posts of Facebook Ads users and Like Farm users attract many more Likes than those of baseline users.

Figure 5 shows the distributions of the number of posts that are classified as “shared activity,” i.e., posts originally made by another user, or articles, images, or videos linked from an external URL (e.g., a blog or YouTube). Figure 5 reveals that baseline users generate more original posts, and a uniform use of tokens across topics in the users’ timelines. Notably, both Figures 2(a) and 2(b) reveal that Like Farm accounts have distinctive behavior compared to normal Facebook users. High diversity in 70% of the topics suggests that token use is much more diverse across the baseline user posts than in Like Farm users’ posts. We also observe, in Figure 2(b), that posts from SF campaigns (SF-ALL and SF-USA) are indistinguishable, with identical distributions, whereas MS users’ posts are clearly distinct, comprising a smaller diversity of tokens.

We acknowledge that our analysis is limited to English-only content and may be statistically biased toward native English speakers. While it should be extended to other languages, we argue that it provides a good indication of lexical differences across categories of users, while developing algorithms for language detection and processing on non-English posts is out of the scope of this paper.

3.2 Interactions with Posts

Table 2: Lexical analysis of Like Farms timelines.

<table>
<thead>
<tr>
<th>Campaign</th>
<th>Avg. sentence length</th>
<th>% of upper case letters</th>
<th>% of punctuation</th>
<th>% of non-letters</th>
<th>Lexical richness</th>
<th>ARI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>19.62</td>
<td>17.15</td>
<td>17.74</td>
<td>18.87</td>
<td>0.23</td>
<td>16.11</td>
</tr>
<tr>
<td>AL-ALL</td>
<td>11.05</td>
<td>19.67</td>
<td>7.59</td>
<td>8.71</td>
<td>0.19</td>
<td>13.09</td>
</tr>
<tr>
<td>AL-USA</td>
<td>14.45</td>
<td>11.61</td>
<td>5.78</td>
<td>6.8</td>
<td>0.13</td>
<td>13.41</td>
</tr>
<tr>
<td>BL-USA</td>
<td>19.66</td>
<td>14.20</td>
<td>5.04</td>
<td>5.61</td>
<td>0.13</td>
<td>13.91</td>
</tr>
<tr>
<td>MS-USA</td>
<td>13.85</td>
<td>12.33</td>
<td>5.81</td>
<td>7.02</td>
<td>0.14</td>
<td>13.23</td>
</tr>
<tr>
<td>SF-ALL</td>
<td>7.53</td>
<td>16.61</td>
<td>11.02</td>
<td>11.62</td>
<td>0.12</td>
<td>13.39</td>
</tr>
<tr>
<td>SF-USA</td>
<td>7.53</td>
<td>15.73</td>
<td>11.05</td>
<td>11.74</td>
<td>0.12</td>
<td>13.36</td>
</tr>
</tbody>
</table>

**Figure 2:** Cumulative distributions of topic entropy.

**Figure 1:** Characterization of timeline posts.
share fewer posts of other users or links, compared to users in the Facebook Ads or Like Farm campaigns.

In Figure 6, we plot the frequency in which users are tagged in posts by others. Figure 6(a) shows that about 95% of baseline users have never been tagged, or were only tagged once. In contrast, around 50% of Like Farm and Facebook Ads users were tagged more than once. This suggests that users from these campaigns are more likely to be tagged or tag their friends on their timeline activity than normal users. This is confirmed by Figures 6(b) and 6(c), which show that around two-thirds of users in FB-EGY and MS-USA have been tagged multiple times.

3.3 Clustering Campaigns

In order to systematically study the liking behavior of users from Like Farms, we cluster their liking activity in our crawls. We aim to identify groups of pages liked by Like Farm users, in both old and new crawls (described in Section 2). To this end, for each campaign, we use a bi-clustering algorithm [13] to group the user-page bipartite graph into distinct clusters. As reported in prior work [2], clustering the user-page bipartite graph identifies near-bipartite cores.
where a subset of users like the same set of pages. We used the silhouette coefficient to determine the optimal number of clusters to form. The algorithm clustered the liking activity of all campaigns in 2 clusters, except for FB-ALL campaign with 8 clusters and SF-ALL campaign with 4 clusters.

Figure 7 visualizes clustering results for a few campaigns using user-page scatter plots. We do not observe a “liking everything” behavior (vertical streaks), which we assume would be easy to detect by fraud detection algorithms [2,20], whereas, we note several instances of a “everyone liking a particular page” behavior (horizontal streaks). For instance, the SF-ALL (old) and BL-USA (new) campaigns have several horizontal streaks, which may be related to users liking popular pages aiming to mimic normal profiles. For instance, horizontal streaks in BL-USA (new) include popular pages such as “Fast & Furious” and “SpongeBob SquarePants”, with millions of likes. We also suspect that horizontal streaks emerge as Like Farm operators need to provide large numbers of Likes. We also notice very clear cluster separation for some campaigns, i.e., a few users like a certain subset of pages. For instance, FB-ALL (new) campaign is grouped into 2 clusters and FB-ALL (old) campaign is grouped into 8 clusters. For Facebook Ad campaigns, this behavior is likely due to Facebook’s ad targeting algorithms, as each cluster may represent a community of users to which Facebook’s algorithms display ads. Moreover, we observe some separation in SF-ALL (new) campaign, where a group of pages have similar liking patterns. For Like Farm campaigns, this behavior may be related to different people (humans) managing subsets of users.

We further analyze main properties of pages grouped into different clusters, including their Like count, categories, and locations—features we collect by crawling publicly available information of these pages (using the Facebook Graph API). Figure 8 plots a representative distribution of Like count and Like ratio of two BL-USA (new) clusters. Like count is the popularity measure of a page, whereas, like ratio indicates the fraction of page Likes contributed by the Like Farm users. We note that cluster 1 pages in BL-USA (new) are significantly more popular than cluster 2 pages, however, Likes contributed by the Like Farm users are responsible for a much higher ratio for cluster 2 pages than cluster 1 pages. This pattern indicates that pages in cluster 2 more likely include paid Like Farm campaign pages. For BL-USA (new) campaign, pages with horizontal streaks include niche pages, e.g., OCSlimwraps (Shannon Carlin Slim Wraps) and mayadphotography (Maya D Photography). We suspect that these pages in cluster 2 are part of Like Farm campaigns. Finally, note that we have also analyzed other information about these pages, such as their categories and location, but find no significant differences across clusters.

4 We omit discussion of other campaigns due to space constraints.

4. RELATED WORK
Prior work has focused on the analysis and detection of fake and sybil accounts in social networks [4,5,23], as well
as spam in Facebook [10] and Twitter [22]. Also, [14, 17] rely on honeypots to actively detect spammers. Stringhini et al. [16, 18] analyze services selling Twitter followers, and Thomas et al. [19] study trafficking of fake and compromised Twitter accounts.

Specific to Facebook fraud is the work by Beutel et al. [2] who introduce CopyCatch, a tool currently deployed by Facebook to detect fraudulent accounts, and show that it can detect fake Likes by identifying groups of connected users liking a set of pages within a short time frame. SynchroTrap [6] extends CopyCatch by clustering accounts that perform similar, possibly malicious, actions. Several other algorithms also aim to detect lockstep behavior using temporal features, including recent ones [11, 12]. Viswanath et al. [20] use unsupervised anomaly detection techniques to distinguish malicious behavior from normal, which can be used to detect compromised, fake, and colluding accounts.

Wang et al. [21] study human involvement in Weibo’s reputation manipulation services, showing that simple evasion attacks (with workers modifying their behavior), as well as powerful poisoning attacks (with administrators tampering with the training set) can severely affect the effectiveness of machine learning algorithms to detect malicious crowdsourcing workers.

In our prior work [9], we have presented a honeypot-based measurements of Likes garnered via four Like Farms and five (legitimate) Facebook Ads campaigns. As discussed earlier, some Like Farms exhibit a stealthy behavior, possibly to circumvent detection techniques (like CopyCatch and SynchroTrap), by avoiding lockstep behavior and liking sets of seemingly random pages. Our work extends [9] as we analyze the liking behavior of users in these campaigns to detect patterns that reveal collusion among users, by clustering them according to the same sets of pages they liked, and study the interaction with timeline activities in comparison to a baseline of normal Facebook users.

5. CONCLUDING REMARKS

In this paper, we presented an in-depth analysis of potentially malicious Facebook accounts, collected via honeypots from several Like Farms and Facebook Ads campaigns [9]. Compared to a baseline of normal Facebook users, we uncovered a few significant characteristics and behaviors of accounts used for reputation manipulation, in terms of timeline activities, interaction with other users, and content of their posts. We unveiled, via a clustering analysis, a potential counter-attack to automatic detection tools, such as CopyCatch [2] and SynchroTrap [6], as accounts from the same Like Farms like very popular pages or relatively niche pages. Through our clustering analysis, we also illustrated the challenges faced by detection tools to effectively identify suspicious accounts, since a large number of Like Farm accounts are still active even after one year.

We found that Like Farm accounts post text with significantly lower lexical richness and entropy, and are much more interactive than regular users. This suggests the opportunity to incorporate, in malicious/fake account detection tools, not only activity thresholds, but also other features such as lexical analysis, which is part of our future work. In conclusion, our study provides an important first step for the detection of stealthy Like Farm campaigns and networks, as a whole.

6. REFERENCES