Social Turing Tests: Crowdsourcing Sybil Detection

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Abstract

As popular tools for spreading spam and malware, Sybils (or fake accounts) pose a serious threat to online communities such as Online Social Networks (OSNs). Today, sophisticated attackers are creating realistic Sybils that effectively befriend legitimate users, rendering most automated Sybil detection techniques ineffective. In this paper, we explore the feasibility of a crowdsourced *Sybil detection system for OSNs. We conduct a large user study on the ability of humans to detect today's Sybil accounts, using a large corpus of ground-truth Sybil accounts from the Facebook and Renren networks. We analyze detection accuracy by both "experts" and "turkers" under a variety of conditions, and find that while turkers vary significantly in their effectiveness, experts consistently produce near-optimal results. We use these results to drive the design of a multi-tier crowdsourcing Sybil detection system. Using our user study data, we show that this system is scalable, and can be highly effective either as a standalone system or as a complementary technique to current tools.*

1 Introduction

The rapid growth of Sybil accounts is threatening the stability and security of online communities, particularly online social networks (OSNs). Sybil accounts represent fake identities that are often controlled by a small number of real users, and are increasingly used in coordinated campaigns to spread spam and malware [6, 30]. In fact, measurement studies have detected hundreds of thousands of Sybil accounts in different OSNs around the world [3,31]. Recently, Facebook revealed that up to 83 million of its users may be fake[1], up significantly from 54 million earlier[2].

[1] http://www.bbc.com/news/technology-19093078
[2] http://www.bbc.com/news/technology-18813237

The research community has produced a substantial number of techniques for automated detection of Sybils [4, 32, 33]. However, with the exception of SybilRank [3], few have been successfully deployed. The majority of these techniques rely on the assumption that Sybil accounts have difficulty friending legitimate users, and thus tend to form their own communities, making them visible to community detection techniques applied to the social graph [29].

Unfortunately, the success of these detection schemes is likely to decrease over time as Sybils adopt more sophisticated strategies to ensnare legitimate users. First, early user studies on OSNs such as Facebook show that users are often careless about who they accept friendship requests from [2]. Second, despite the discovery of Sybil communities in Tuenti [3], not all Sybils band together to form connected components. For example, a recent study of half a million Sybils on the Renren network [14] showed that Sybils rarely created links to other Sybils, and instead intentionally try to infiltrate communities of legitimate users [31]. Thus, these Sybils rarely connect to each other, and do not form communities. Finally, there is evidence that creators of Sybil accounts are using advanced techniques to create more realistic profiles, either by copying profile data from existing accounts, or by recruiting real users to customize them [30]. Malicious parties are willing to pay for these authentic-looking accounts to better befriend real users.

These observations motivate us to search for a new approach to detecting Sybil accounts. Our insight is that while attackers are creating more "human" Sybil accounts, fooling intelligent users, *i.e.* passing a "social Turing test," is still a very difficult task. Careful users can apply intuition to detect even small inconsistencies or discrepancies in the details of a user profile. Most online communities already have mechanisms for users to "flag" questionable users or content, and social networks often employ specialists dedicated to identifying malicious content and users [3]. While these mechanisms are ad hoc and costly, our goal is to explore a scalable and systematic approach of applying human effort, *i.e.* crowdsourcing, as a tool to detect Sybil accounts.

Designing a successful crowdsourced Sybil detection requires that we first answer fundamental questions on issues of accuracy, cost, and scale. One key question is, how accurate are users at detecting fake accounts? More specifically, how is accuracy impacted by factors such as the user's experience with social networks, user motivation, fatigue, and language and cultural barriers? Second, how much would it cost to crowdsource authenticity checks for all suspicious profiles? Finally, how can we design a crowdsourced Sybil detection system that scales to millions of profiles?

In this paper, we describe the results of a large user study into the feasibility of crowdsourced Sybil detection. We gather ground-truth data on Sybil accounts from *three* social network populations: Renren [14], the largest social network in China, Facebook-US, with profiles of English speaking users, and Facebook-India, with profiles of users who reside in India. The security team at Renren Inc. provided us with Renren Sybil account data, and we obtained Facebook (US and India) Sybil accounts by crawling highly suspicious profiles weeks before they were banned by Facebook. Using this data, we perform user studies analyzing the effectiveness of Sybil detection by three user populations: motivated and experienced "experts"; crowdsourced workers from China, US, and India; and a group of UCSB undergraduates from the Department of Communications.

Our study makes three key contributions. First, we analyze detection accuracy across different datasets, as well as the impact of different factors such as demographics, survey fatigue, and OSN experience. We found that well-motivated experts and undergraduate students produced exceptionally good detection rates with near-zero false positives. Not surprisingly, crowdsourced workers missed more Sybil accounts, but still produced near zero false positives. We observe that as testers examine more and more suspicious profiles, the time spent examining each profile decreases. However, experts maintained their accuracy over time while crowdworkers made more mistakes with additional profiles. Second, we performed detailed analysis on individual testers and account profiles. We found that while it was easy to identify a subset of consistently accurate testers, there were very few "chameleon profiles" that were undetectable by all test groups. Finally, we propose a scalable crowdsourced Sybil detection system based on our results, and use trace-driven data to show that it achieves both accuracy and scalability with reasonable costs.

By all measures, Sybil identities and fake accounts are growing rapidly on today's OSNs. Attackers continue to innovate and find better ways of mass-producing fake profiles, and detection systems must keep up both in terms of accuracy and scale. This work is the first to propose crowdsourcing Sybil detection, and our user study results are extremely positive. We hope this will pave the way towards testing and deployment of crowdsourced Sybil detection systems by large social networks.

2 Background and Motivation

Our goal is to motivate and design a crowdsourced Sybil detection system for OSNs. First, we briefly introduce the concept of crowdsourcing and define key terms. Next, we review the current state of social Sybil detection, and highlight ongoing challenges in this area. Finally, we introduce our proposal for crowdsourced Sybil detection, and enumerate the key challenges to our approach.

2.1 Crowdsourcing

Crowdsourcing is a process where work is outsourced to an undefined group of people. The web greatly simplifies the task of gathering virtual groups of workers, as demonstrated by successful projects such as Wikipedia. Crowdsourcing works for any job that can be decomposed into short, simple tasks, and brings significant benefits to tasks not easily performed by automated algorithms or systems. First, by harnessing small amounts of work from many people, no individual is overburdened. Second, the group of workers can change dynamically, which alleviates the need for a dedicated workforce. Third, workers can be recruited quickly and on-demand, enabling elasticity. Finally and most importantly, by leveraging human intelligence, crowdsourcing can solve problems that automated techniques cannot.

In recent years, crowdsourcing websites have emerged that allow anyone to post small jobs to the web and have them be solved by crowdworkers for a small fee. The pioneer in the area is Amazon's Mechanical Turk, or *MTurk* for short. On MTurk, anyone can post jobs called Human Intelligence tasks, or *HITs*. Crowdworkers on MTurk, or *turkers*, complete HITs and collect the associated fees. Today, there are around 100,000 HITs available on MTurk at any time, with 90% paying $\leq$\$0.10 each [11, 24]. There are over 400,000 registered turkers on MTurk, with 56% from the US, and 36% from India [24].

Social networks have started to leverage crowdsourcing to augment their workforce. For example, Facebook crowdsources content moderation tasks, including filtering pornographic and violent pictures and videos [10]. However, to date we know of no OSN that crowdsources the identification of fake accounts. Instead, OSNs like Facebook and Tuenti maintain dedicated, in-house staff for this purpose [3, 10].

Unfortunately, attackers have also begun to leverage crowdsourcing. Two recent studies have uncovered crowdsourcing websites where malicious users pay crowdworkers to create Sybil accounts on OSNs and generate spam [21, 30]. These Sybils are particularly dangerous because they are created and managed by real human beings, and thus appear more authentic than those created by automated scripts. Crowdsourced Sybils can also bypass traditional security mechanisms, such as CAPTCHAs, that are designed to defend against automated attacks.

2.2 Sybil Detection

The research community has produced many systems designed to detect Sybils on OSNs. However, each one relies on specific assumptions about Sybil behavior and graph structure in order to function. Thus, none of these systems is general enough to perform well on all OSNs, or against Sybils using different attack strategies.

The majority of social Sybil detectors from the literature rely on two key assumptions. First, they assume that Sybils have trouble friending legitimate users. Second, they assume that Sybil accounts create many edges amongst themselves. This leads to the formation of well-defined Sybil communities that have a small quotient-cut from the honest region of the graph [4, 28, 29, 32, 33]. Although similar Sybil community detectors have been shown to work well on the Tuenti OSN [3], other studies have demonstrated limitations of this approach. For example, a study by Yang et al. showed that Sybils on the Renren OSN do not form connected components at all [31]. Similarly, a meta-study of multiple OSN graphs revealed that many are not fast-mixing, which is a necessary precondition for Sybil community detectors to perform well [20].

Other researchers have focused on feature-based Sybil detectors. Yang et al. detect Sybils by looking for accounts that send many friend requests that are rejected by the recipient. This detection technique works well on Renren because Sybils must first attempt to friend many users before they can begin effectively spamming [31]. However, this technique does not generalize. For example, Sybils on Twitter do not need to create social connections, and instead send spam directly to any user using "@" messages.

Current Sybil detectors rely on Sybil behavior assumptions that make them vulnerable to sophisticated attack strategies. For example, Irani et al. demonstrate that "honeypot" Sybils are capable of passively gathering legitimate friends and penetrating the social graph [13]. Similarly, some attackers pay users to create fake profiles that bypass current detection methods [30]. As Sybil creators adopt more sophisticated strategies, current techniques are likely to become less effective.

2.3 Crowdsourcing Sybil Detection

In this study, we propose a crowdsourced Sybil detection system. We believe this approach is promising for three reasons: first, humans can make overall judgments about OSN profiles that are too complex for automated algorithms. For example, humans can evaluate the sincerity of photographs and understand subtle conversational nuances. Second, social-Turing tests are resilient to changing attacker strategies, because they are not reliant on specific features. Third, crowdsourcing is much cheaper than hiring full-time content moderators [9, 25]. However, there are several questions that we must answer to verify that this system will work in practice:

- How **accurate** are users at distinguishing between real and fake profiles? Trained content moderators can perform this task, but can crowdworkers achieve comparable results?
- Are there **demographic factors** that affect detection accuracy? Factors like age, education level, and OSN experience may impact the accuracy of crowdworkers.
- Does **survey fatigue** impact detection accuracy? In many instances, people's accuracy at a task decline over time as they become tired and bored.
- Is crowdsourced Sybil detection **cost effective**? Can the system be scaled to handle OSNs with hundreds of millions of users?

We answer these questions in the following sections. Then, in Section 6, we describe the design of our crowdsourced Sybil detection system, and use our user data to validate its effectiveness.

3 Experimental Methodology

In this section, we present the design of our user studies to validate the feasibility of crowdsourced Sybil detection. First, we introduce the three datasets used in our experiments: Renren, Facebook US, and Facebook India. We describe how each dataset was gathered, and how the ground-truth classification of Sybil and legitimate profiles was achieved. Next, we describe the high-level design of our user study and its website implementation. Finally, we introduce the seven groups of test subjects. Test subjects are grouped into experts, turkers from crowdsourcing websites, and university undergraduates. We use different test groups from China, the US, and India that correspond to our three datasets. All of our data collection and experimental methodology was evaluated and received IRB approval before we commenced our study.

3.1 Ground-truth Data Collection

Our experimental datasets are collected from two large OSNs: Facebook and Renren. Facebook is the most popular OSN in the world and has more than 1 billion users [8]. Renren is the largest OSN in China, with more than 220

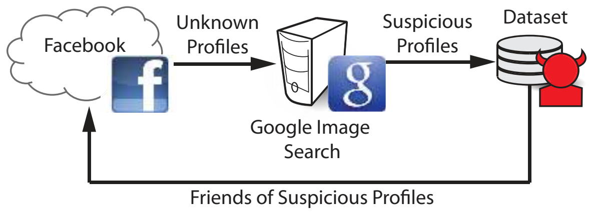


Figure 1. Facebook crawling methodology.

million users [14]. Both sites use similar visual layouts and offer user profiles with similar features, including space for basic information, message "walls," and photo albums. Basic information in a profile includes items like name, gender, a profile image, total number of friends, interests, *etc*.

Each dataset is composed of three types of user profiles: confirmed *Sybils*, confirmed *legitimate* users, and *suspicious* profiles that are likely to be Sybils. Confirmed Sybil profiles are known to be fake because they have been banned by the OSN in question, and manually verified by us. Suspicious profiles exhibit characteristics that are highly indicative of a Sybil, but have not been banned by the OSN. Legitimate profiles have been hand selected and verified by us to ensure their integrity. We now describe the details of our data collection process on Facebook and Renren.

Facebook. We collect data from Facebook using a custom web crawler. Because Facebook caters to an international audience, we specifically targeted two regional areas for study: the US and India. We chose these two regions because they have large, Internet enabled populations, and both countries have active marketplaces for crowdworkers [24]. Our Facebook crawls were conducted between December 2011 and January 2012.

The legitimate profiles for our study were randomly selected from a pool of 86K profiles. To gather this pool of profiles, we seeded our crawler with 8 Facebook profiles belonging to members of our lab (4 in the US, and 4 in India). The crawler then visited each seed's friends-of-friends, *i.e.* the users two-hops away on the social graph. Studies have shown that trust on social networks is often transitive [18], and thus the friends-of-friends of our trusted seeds are likely to be trustworthy as well. From the 86K total friends-of-friends in this set, the crawler sampled 100 profiles (50 from the US, 50 from India) that had Facebook's default, permissive privacy settings. We manually examined all 100 profiles to make sure they were 1) actually legitimate users, and 2) we did not know any of them personally (to prevent bias in our study).

To facilitate collection of Sybils on Facebook, we make one assumptions about Sybil behavior: we assume that Sybils use *widely available photographs* from the web as profile images. Intuitively, Sybils need realistic profile images in order to appear legitimate. Hence, Sybils must resort to using publicly available images from around the web. Although *all* Sybils on Facebook may not obey this assumption, we will show that enough do to form a sufficiently large sample for our user study.

To gather suspicious profiles, we seeded our crawler with the profiles of known Sybils on Facebook [1]. The crawler then snowball crawled outward from the initial seeds. We leveraged *Google Search by Image* to locate profiles using widely available photographs as profile images. Figure 1 illustrates this process. For each profile visited by the crawler, *all* of its profile images were sent to Google Search by Image (Facebook maintains a photo album for each user that includes their current profile image, as well as all prior images). If Google Search by Image indexed $\geq$90% of the profile images on sites other than Facebook, then we consider the account to be suspicious. The crawler recorded the basic information, wall, and photo albums from each suspicious profile. We terminated the crawl after a sufficient number of suspicious profiles had been located.

We search for all of a user's profile images rather than just the current image because legitimate users sometimes use stock photographs on their profile (*e.g.* a picture of their favorite movie star). We eliminate these false positives by setting minimum thresholds for suspicion: we only consider profiles with $\geq$2 profile images, and if $\geq$90% are available on the web, then the profile is considered suspicious.

In total, our crawler was able to locate 8779 suspicious Facebook profiles. Informal, manual inspection of the profile images used by these accounts reveals that most use pictures of ordinary (usually attractive) people. Only a small number of accounts use images of recognizable celebrities or non-people (*e.g.* sports cars). Thus, the majority of profile images in our dataset are not suspicious at first-glance. Only by using external information from Google does it become apparent that these photographs have been misappropriated from around the web.

At this point, we don't have ground-truth about these profiles, *i.e.* are they really Sybils? To determine ground-truth, we use the methodology pioneered by Thomas *et al.* to locate fake Twitter accounts [27]. We monitored the suspicious Facebook profiles for 6 weeks, and observed 573 became inaccessible. Attempting to browse these profiles results in the message "The page you requested was not found," indicating that the profile was either removed by Facebook or by the owner. Although we cannot ascertain the specific reason that these accounts were removed, the use of widely available photographs as profile images makes it highly likely that these 573 profiles are fakes.

The sole limitation of our Facebook data is that it only includes data from public profiles. It is unknown if the characteristics of private accounts (legitimate and Sybil) differ from public ones. This limitation is shared by all studies that rely on crawled OSN data.

Renren. We obtained ground-truth data on Sybil and

Dataset	# of Profiles Sybil	Legit.	Test Group	# of Testers	Profiles per Tester
Renren	100	100	CN Expert	24	100
			CN Turker	418	10
Facebook US	32	50	US Expert	40	50
			US Turker	299	12
			US Social	198	25
Facebook IN	50	50	IN Expert	20	100
			IN Turker	342	12

Table 1. Datasets, test groups, and profiles per tester.

Dataset	Category	News-Feed	Photos	Profile Images	Censored Images
Renren	Legit.	165	302	10	0
	Sybil	30	22	1.5	0.06
Facebook US	Legit.	55.62	184.78	32.86	0
	Sybil	60.15	10.22	4.03	1.81
Facebook IN	Legit.	55	53.37	7.27	0
	Sybil	31.6	10.28	4.44	0.08

Table 2. Ground-truth data statistics (average number per profile).

legitimate profiles on Renren directly from Renren Inc. The security team at Renren gave us complete information on 1082 banned Sybil profiles, from which we randomly selected 100 for our user study. Details on how Renren bans Sybil accounts can be found in [31]. We collected legitimate Renren profiles using the same methodology as for Facebook. We seeded a crawler with 4 trustworthy profiles from people in the lab, crawled 100K friends-of-friends, and then sampled 100 public profiles. We forwarded these profiles to Renren's security team and they verified that the profiles belonged to real users.

Summary and Data Sanitization. Table 1 lists the final statistics for our three datasets. Since the Renren data was provided directly by Renren Inc., all profiles are confirmed as either Sybils or legitimate users. For Facebook US and India, profiles that were banned by Facebook are confirmed Sybils, and the remaining unconfirmed suspicious profiles are not listed.

During our manual inspection of profiles, we noticed that some include images of pornography or graphic violence. We determined that it was not appropriate for us to use these images as part of our user study. Thus, we manually replaced objectionable images with a grey image containing the words "Pornographic or violent image removed." This change protects our test subjects from viewing objectionable images, while still allowing them to get a sense of the original content that was included in the profile. Out of 45,096 total images in our dataset, 58 are filtered from Facebook US, 4 from Facebook India, and 6 from Renren. All objectionable images are found on Sybil profiles; none are found on legitimate profiles.

Finally, we show the basic statistics of ground-truth profiles in Table 2. Legitimate users have more photo albums and profile photos, while Sybils have more censored photos. The "News-Feed" column shows the average number of items in the first 5 chronological pages of each user's news-feed. On Facebook, the news-feed includes many types of items, including wall posts, status updates, photo tags, *etc*. On Renren, the feed *only* includes wall posts from friends.

3.2 Experiment Design

Using the datasets in Table 1, our goal is to assess the ability of humans to discriminate between Sybil and legitimate user profiles. To test this, we perform a simple, controlled study: we show a human test subject (or simply a *tester*) a profile from our dataset, and ask them to classify it as real or fake. The tester is allowed to view the profile's basic information, wall, photo albums, and individual photos before making their judgment. If the tester classifies the profile as fake, they are asked what profile elements (basic information, wall, or photos) led them to this determination.

Each tester in our study is asked to evaluate several profiles from our dataset, one at a time. Each tester is given roughly equal number of Sybil profiles and legitimate profiles. The profiles from each group are randomized for each tester, and the order the profiles are shown in is also randomized.

Implementation. We implement our study as a website. When a tester begins the study, they are presented with a webpage that includes a consent form and details about our study. After the tester agrees, they are directed to the first profile for them to evaluate. Figure 2 shows a screenshot of our evaluation page. At the top are links to the all of the profiles the tester will evaluate. Testers may use these links to go back and change their earlier answers if they wish.

Below the numbered links is a box where testers can record their evaluation for the given profile: real or fake, and if fake, what profile elements are suspicious (profile, wall, and/or photos)? When the tester is done evaluating the given profile, they click the "Save Changes" button, which automatically directs their browser to the next profile, or the end of the survey if all profiles have been evaluated.

Below the evaluation box are three buttons that allow the tester to view the given profile's basic information (shown by default), wall, and photo albums. The basic information and wall are presented as JPEG images, in order to preserve the exact look of Facebook/Renren, while also preventing the tester from clicking any (potentially malicious) embedded links. Testers may click on each photo album to view the individual photos contained within.

Figure 2. Screenshot of the English version of our user study website.

At the end of the survey, the tester is asked to answer a short questionnaire of demographic information. Questions include age, gender, country of residence, education level, and years of OSN experience. There is also a free-form comment box where tester can leave feedback.

On the server-side, we record all of the classifications and questionnaire answers made by each tester. We also collect additional information such as the time spent by the tester on each page, and total session time per tester.

Because our datasets are in two different languages, we construct two versions of our study website. Figure 2 shows the English version of our site, which is used to evaluate Facebook profiles. We also constructed a Chinese version of our site to evaluate Renren profiles.

Limitations. The methodology of our user study has two minor limitations. First, we give testers full profiles to evaluate, including basic info, wall, and photos. It is not clear how accurate testers would be if given different information, or a restricted subset of this information. Second, we assume that there are no malicious testers participating in our user study. Although attackers might want to infiltrate and disrupt a real crowdsourced Sybil detector, there is little for them to gain by disrupting our study. Related work on detecting crowdsourcing abuse may be helpful in mitigating this problem in the future [7].

3.3 Test Subjects

In order to thoroughly investigate how accurate different types of users are at detecting Sybils, we ran user studies on three different groups of test subjects. Each individual tester was asked to evaluate $\geq$10 profiles from our dataset, and each profile was evaluated by multiple testers from each group. This allows us to examine the overall detection accuracy of the group (*e.g.* the crowd), versus the accuracy of each individual tester. We now introduce the three test groups, and explain how we administered our study to them.

Experts. The first group of test subjects are *experts*. This group contains Computer Science professors and graduate students that were carefully selected by us. The expert group represents the practical upper-bound on achievable Sybil detection accuracy.

The expert group is subdivided into three regional groups: US, Indian, and Chinese experts. Each expert group was evaluated on the corresponding regional dataset. We approached experts in person, via email, or via social media and directed them to our study website to take the test. Table 1 lists the number of expert testers in each regional group. Expert tests were conducted in February, 2012.

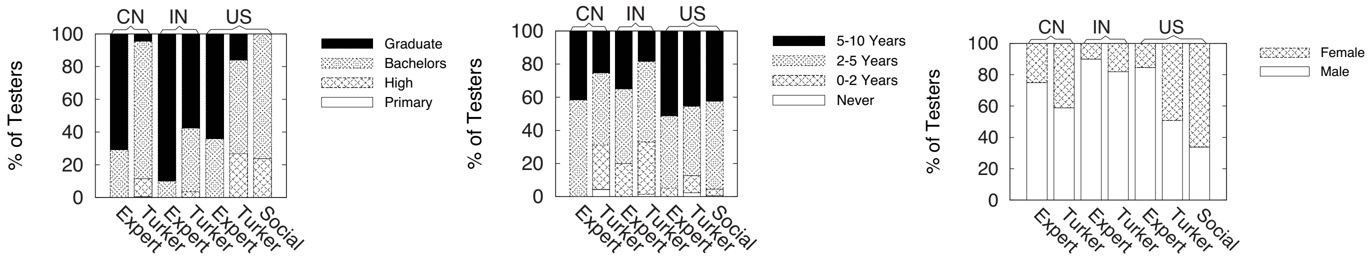
As shown in Table 1, each Chinese and Indian expert evaluated 100 profiles from our dataset, while US experts evaluated 50 profiles. This is significantly more profiles per tester than we gave to any other test group. However, since experts are dedicated professionals, we assume that their accuracy will not be impacted by survey fatigue. We evaluate this assumption in Section 5.

Turkers. The second group of test subjects are *turkers* recruited from crowdsourcing websites. Unlike the expert group, the background and education level of turkers cannot be experimentally controlled. Thus, the detection accuracy of the turker group provides a lower-bound on the efficacy of a crowdsourced Sybil detection system.

Like the expert group, the turker group is subdivided into three regional groups. US and Indian turkers were recruited from MTurk. HITs on MTurk may have *qualifications* associated with them. We used this feature to ensure that only US based turkers took the Facebook US test, and Indian turkers took the Facebook India test. We also required that turkers have $\geq$90% approval rate for their HITs, to filter out unreliable workers. We recruited Chinese turkers from *Zhubajie*, the largest crowdsourcing site in China. Table 1 lists the number of turkers who completed our study in each region. Turker tests were conducted in February, 2012.

Unlike the expert groups, turkers have an incentive to sacrifice accuracy in favor of finishing tasks quickly. Because turkers work for pay, the faster they complete HITs, the more HITs they can do. Thus, of all our test groups, we gave turkers the fewest number of profiles to evaluate, since turkers are most likely to be effected by survey fatigue. As shown in Table 1, Chinese turkers each evaluated 10 profiles, while US and Indian turkers evaluated 12.

We priced each Zhubajie HIT at \$0.15 (\$0.015 per profile), and each MTurk HIT at \$0.10 (\$0.0083 per profile). These prices are in line with the prevailing rates on crowd-



(a) Education Level (b) OSN Usage Experience (c) Gender

Figure 3. Demographics of participants in our user study.

sourcing websites [11]. Although we could have paid more, prior work has shown that paying more money does not yield higher quality results on crowdsourcing sites [19].

Sociology Undergraduates. The final group of test subjects are undergraduate students from the Department of Communications at UCSB (Social Science major). These students were asked to take our study in exchange for course credit. This group adds additional perspective to our study, apart from Computer Science oriented experts and the uncontrolled turker population.

The social science students are listed in Table 1 as “US social.” We only asked the students to evaluate our Facebook US dataset, since cultural and language barriers prevent them from effectively evaluating Chinese and Indian profiles. 198 total students completed our study in March, 2012. Each student was asked to evaluate 25 profiles, midway between what we asked of experts and turkers.

Summary. We conduct experiments with 7 groups of testers: experts from US, India, and China; turkers from US, India, and China, and social science students from the US. Table 1 lists the number of testers in each group and the number of profiles evaluated by each tester.

4 User Study Results

In this section, we present the high level results of our user study. We start by introducing the demographics of the test subjects. Next, we address one of our core questions: how accurate are people at identifying Sybils? We compare the accuracy of individual testers to the accuracy of the group to assess whether the “wisdom of the crowd” can overcome individual classification errors. Finally, we examine the reasons testers cited in classified profiles as Sybils.

4.1 Demographics

At the end of each survey, testers were asked to answer demographic questions about themselves. Figure 3 shows the results that were self-reported by testers.

Education. As shown in Figure 3(a), most of our experts are enrolled in or have received graduate level degrees. This is by design, since we only asked Computer Science graduate students, undergrads enrolled in graduate courses, and professors to take part in our expert experiments. Similarly, the social science testers are drawn from the undergraduate population at UCSB, which is reflected in the results.

The education levels reported by turkers are surprisingly high. The majority of turkers in the US and China report enrollment or receipt of bachelors-level degrees [24]. Surprisingly, over 50% of Indian turkers report graduate level educations. This result for Indian turkers stems from cultural differences in how education levels are denoted. Unlike in the US and China, in India “graduate school” refers to “graduated from college,” not receipt of a post-graduate degree (*e.g.* Masters or Doctorate). Thus, most “graduate” level turkers in India are actually bachelors level.

OSN Usage Experience. As shown in Figure 3(b), the vast majority of testers report extensive experience with OSNs. US experts, Chinese experts, and social science undergrads almost uniformly report $\geq$2 years of OSN experience. Indian experts, Indian turkers, and Chinese turkers have the greatest fractions of users with $<$2 years of OSN experience. US turkers report levels of OSN experience very similar to our most experienced expert groups.

Gender. As shown in Figure 3(c), the vast majority of our testers are male. The only group which exhibits a female majority is the social science undergrads, a demographic bias of the communications major. Turker groups show varying levels of gender bias: Chinese and Indian turkers are predominantly male [24], while the US group is evenly divided.

4.2 Individual Accuracy

We now address one of the core questions of the paper: how accurate are people at identifying Sybils? To achieve 100% accuracy, a tester needs to correctly classify all Sybil and legitimate profiles they were shown during the test. Figure 4 shows the accuracy of testers in 5 of our test groups. Chinese experts are the most accurate, with half achieving $\geq$90% accuracy. The US and Indian (not shown) experts also achieved high accuracy. However, the turker groups do

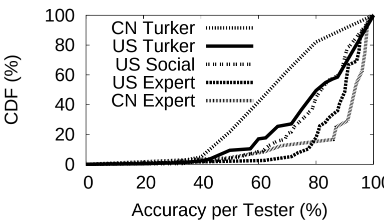
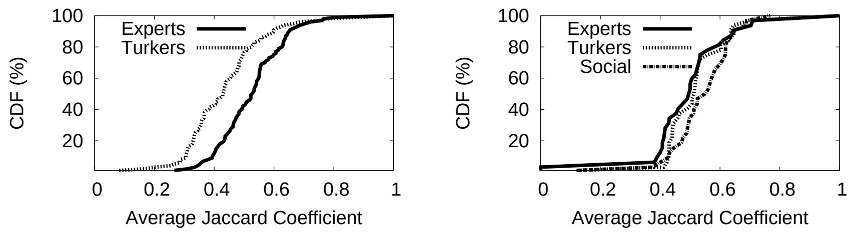


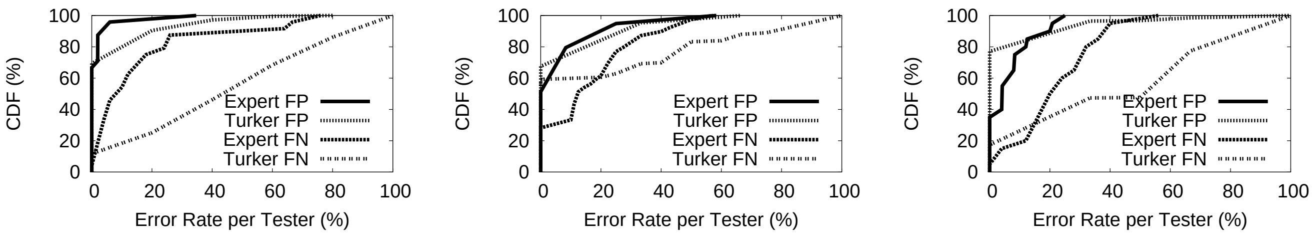
Figure 4. Tester accuracy.



(a) Renren

(b) Facebook US

Figure 5. Jaccard similarity coefficient of reasons.



(a) Renren

(b) Facebook US

(c) Facebook India

Figure 6. False positive (FP) and false negative (FN) rates for testers.

not perform as well as the experts. The Chinese and Indian (not shown) turkers perform the worst, with half achieving ≤65% accuracy. The accuracy of US turkers and social science students falls in-between the other groups.

To better understand tester accuracy, Figure 6 separates the results into false positives and false negatives. A false positive corresponds to misclassifying a legitimate profile as a Sybil, while a false negative means failing to identify a Sybil. Figure 6 focuses on our expert and turker test groups; social science students perform similarly to US turkers, and the results are omitted for brevity.

Figure 6 reveals similar trends across all test groups. First, false positives are uniformly lower than false negatives, *i.e.* testers are more likely to misclassify Sybils as legitimate, than vice versa. Second, in absolute terms, the false positive rates are quite low: <20% for 90% of testers. Finally, as in Figure 4, error rates for turkers tend to be significantly higher than those of experts.

In summary, our results reveal that people can identify differences between Sybil and legitimate profiles, but most individual testers are not accurate enough to be reliable.

4.3 Accuracy of the Crowd

We can leverage "the wisdom of the crowd" to amortize away errors made by individuals. Many studies on crowdsourcing have demonstrated that experimental error can be controlled by having multiple turkers vote on the answer, and then using the majority opinion as the final answer [17, 25]. As long as errors by turkers are uncorrelated, this approach generates very accurate results.

We now examine whether this methodology can be used to improve the classification accuracy of our results. This question is of vital importance, since a voting scheme would be an essential component of a crowdsourced Sybil detector. To compute the "final" classification for each profile in our dataset, we aggregate all the votes for that profile by testers in each group. If ≥50% of the testers vote for fake, then we classify that profile as a Sybil.

Table 3 shows the percentage of false positive and negative classifications for each test group after we aggregate votes. The results are mixed: on one hand, false positive rates are uniformly low across all test groups. In the worst case, US turkers and social science students only misclassify 1 out of 50 legitimate profiles. Practically, this means that crowds can successfully identify real OSN profiles.

On the other hand, false negative rates vary widely across test groups. Experts in China, in the US, and the social science students all perform well, with false negative rates <10%. Indian experts also outperform the turker groups, but only by a 2.7% margin. The Chinese and Indian turker groups perform worst, with ≥50% false negatives.

From these results, we can conclude three things. First, using aggregate votes to classify Sybils *does* improve overall accuracy significantly. Compared to the results for individual testers in Figure 6, both false positive and negative rates are much lower after aggregation. Second, the uniformly low false positive rates are a very good result. This means that running a crowdsourced Sybil detection system will not harm legitimate social network users. Finally, even with aggregate voting, turkers are still not as accurate as ex-

Dataset	Tester	FP Rate	FN Rate
Renren	CN Expert	0%	3%
	CN Turker	0%	63%
Facebook US	US Expert	0%	9.4%
	US Turker	2%	18.7%
	US Social	2%	6.25%
Facebook IN	IN Expert	0%	16%
	IN Turker	0%	50%

Table 3. Error rates after aggregating votes.

Dataset	Tester	Info	Wall	Photos
Renren	CN Expert	18%	57%	25%
	CN Turker	31%	31%	38%
Facebook US	US Expert	37%	30%	33%
	US Turker	35%	32%	33%
	US Social	30%	31%	39%
Facebook IN	IN Expert	39%	28%	33%
	IN Turker	39%	27%	34%

Table 4. Reasons why profiles are suspicious.

perts. In the next section, we look more deeply into factors that may negatively influence turkers accuracy, and techniques that can mitigate these issues.

4.4 Reasons for Suspicion

During our user study, testers were asked to give *reasons* for why they classified profiles as Sybils. Testers were given the option of reporting the profile's basic information, wall, and/or photos as suspicious. Testers could select as many options as they liked.

In this section, we compare and contrast the reasons reported by different test groups. Table 4 shows percentage of votes for each reasons across our seven test groups. The US and Indian expert and turker groups are very consistent: they all slightly favor basic information. The bias may be due to the way our study presented information, since each profile's basic information was shown first, by default. The social science students are the only group that slightly favors photos.

In contrast to the US and Indian groups, Chinese experts and turkers often disagree on their reasons for suspicion. The majority of experts rely on wall messages, while turkers slightly favor photos. As shown in Figure 4, Chinese turkers have lower accuracy than Chinese experts. One possible reason for this result is that turkers did not pay enough attention to the wall. As previously mentioned, there is a comment box at the end of our survey for testers to offer feedback and suggestions. Several Chinese experts left comments saying they observed wall messages asking questions like "do I know you?," and "why did you send me a friend request?," which they relied on to identify Sybil profiles.

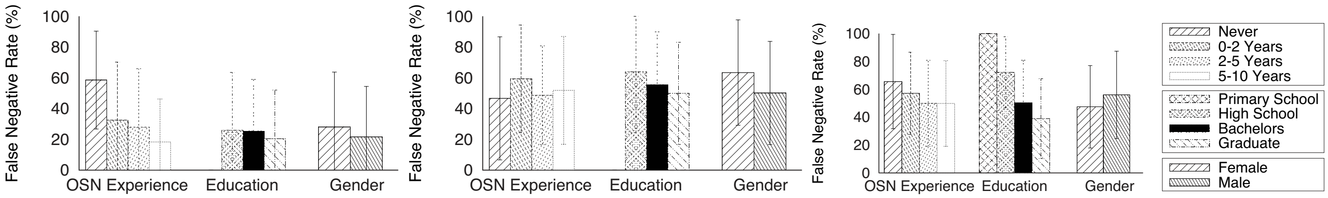
Consistency of Reasons. There is no way to objectively evaluate the correctness of tester's reasons for classification, since there is no algorithm that can pick out suspicious pieces of information from an OSN profile. Instead, what we can do is examine how consistent the reasons are for each profile across our test groups. If all the testers agree on the reasons why a given profile is suspicious, then that is a strong indication that those reasons are correct.

To calculate consistency, we use the following procedure. In each test group, each Sybil is classified by N testers. For all pairs of users in each group that classified a particular Sybil profile, we calculate the Jaccard similarity coefficient to look at overlap in their reasons, giving us $N * (N-1)/2$ unique coefficients. We then compute the average of these coefficients for each profile. By computing the average Jaccard coefficient for each Sybil, we arrive at a distribution of consistency scores for all Sybils for a given test group.

Figure 5 shows the consistency distributions of the China and US test groups. The results for the Indian test groups are similar to US testers, and are omitted for brevity. The Chinese turkers show the most disagreement: for 50% of Sybils the average Jaccard coefficient is $\leq$0.4. Chinese experts and all three US groups exhibit similar levels of agreement: 50% of Sybils have coefficients $\leq$0.5. The fraction of Sybils receiving near complete disagreement (0.0) or agreement (1.0) is negligibly small across all test groups.

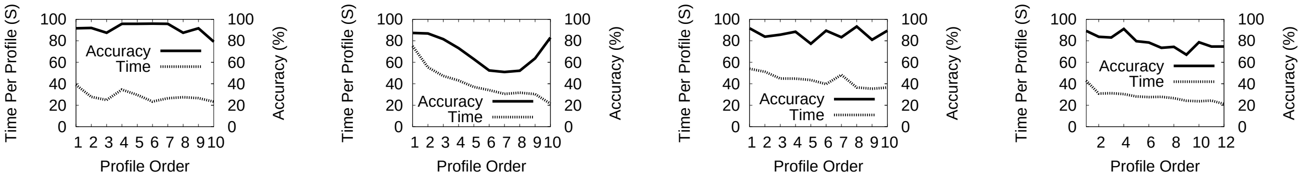
Based on these results, we conclude that testers identify Sybils for inconsistent reasons. Even though Table 4 shows that each of the three available reasons receives a roughly equal portion of votes overall, the reasons are assigned randomly across Sybils in our dataset. This indicates that no single profile feature is a consistent indicator of Sybil activity, and that testers benefit from having a large, diverse set of information when making classifications. Note that this provides further support that automated mechanisms based on individual features are less likely to succeed, and also explains the success of human subjects in detecting Sybils.

Answer Revisions. While taking our survey, testers had the option of going back and changing classifications that they have previously made. However, few took advantage of this feature. This is not unexpected, especially for turkers. Since turkers earn more if they work faster, there is a negative incentive to go back and revise work. In total, there were only 28 revisions by testers: 16 from incorrect to correct, and 12 from correct to incorrect.



(a) US Turker (b) India Turker (c) Chinese Turker

Figure 7. False positive rates for turkers, broken down by demographic.



(a) Renren Expert (b) Renren Turker (c) Facebook US Expert (d) Facebook US Turker

Figure 8. Accuracy and time on the nth profile.

5 Turker Accuracy Analysis

The end goal of our work is to create a crowdsourced Sybil detection system. However, in Section 4 we observed that turkers are not as accurate as experts. In this section, we examine factors that may impact the accuracy of turkers, and investigate ways to improve our Sybil detection system. We start by looking at demographic factors. Next, we examine profile evaluation time to understand if turkers are adversely affected by survey fatigue. Next, we examine issues of turker selection. Will adding more turkers to the crowd improve accuracy? What if we set a threshold and filter out turkers that consistently perform poorly? Finally, we calculate the per profile accuracy of testers to detect "stealth Sybils" that are undetectable by both experts and turkers.

5.1 Demographic Factors

First, we explore the impact of demographic factors on the turker's accuracy. We focus on false negative rates of turkers, since their false positive rates are close to zero. Figure 7 shows the average false negative rate and standard deviation of turkers from China, US and India, broken down by different demographics. Education has a clear impact on false negatives: higher education level correlates with increased ability to identify Sybils. The impact of OSN usage experience is less clear. Chinese and US turker's false negative rates decline as OSN experience increases, which is expected. However, for Indian turkers there is no correlation. Gender does not appear to impact false negatives in a meaningful way. The results in Figure 7 indicate that turker accuracy could be improved by filtering out workers with few years of OSN experience and low education level.

5.2 Temporal Factors and Survey Fatigue

It is known that turkers try to finish tasks as quickly as possible in order to earn more money in a limited amount of time [16]. This leads to our next question: do turkers spend less time evaluating profiles than experts, and does this lead to lower accuracy? The issue of time is also related to survey fatigue: does the accuracy of each tester decrease over time due to fatigue and boredom?

To understand these temporal factors, we plot Figure 8, which shows the average evaluation time and accuracy per profile "slot" for Chinese and US experts and turkers. The x-axis of each subfigure denotes the logical order in which testers evaluated profiles, *e.g.* "Profile Order" n is the n^{th} profile evaluated by each tester. Note that profiles are presented to each tester in random order, so each tester evaluated a different profile within each slot. Within each slot, we calculate the average profile evaluation time and accuracy across all testers. 100% accuracy corresponds to all testers correctly classifying the nth profile they were shown. Although experts evaluated $>$10 profiles each, we only show the first 10 to present a fair comparison versus the turkers. The results for the Indian test groups are similar to the US groups, and are omitted for brevity.

The first important result from Figure 8 is that absolute profile evaluation time is not a good indicator of accuracy. The Chinese experts exhibit the fastest evaluation times, averaging one profile every 23 seconds. However, they are more accurate than Chinese turkers who spend more time on each profile. This pattern is reversed on Facebook: experts spend more time and are more accurate than turkers.

Next, we look for indications of survey fatigue. In all 4 subfigures of Figure 8, the evaluation time per profile decreases over time. This shows that testers speed up as they progress through the survey. As shown in the expert Figures 8(a) and 8(c), this speedup does not affect accuracy. These trends continue through the evaluation of additional profiles (10-50 for Chinese experts, 10-100 for US experts) that are not shown here. However, for turkers, accuracy does tend to decrease over time, as shown in Figures 8(b) and 8(d). This demonstrates that turkers are subject to survey fatigue. The up-tick in Chinese turker accuracy around profile 10 is a statistical anomaly, and is not significant.

5.3 Turker Selection

As demonstrated in Section 4.3, we can mitigate the classification errors of individuals by aggregating their votes together. This raises our next question: can we continue to improve the overall accuracy of turkers by simply adding more of them?

To evaluate this, we conducted simulations using the data from our user study. Let C be the list of classifications received by a given profile in our dataset (either a Sybil or legitimate profile) by a given group of turkers (China, US, or India). To conduct our simulation, we randomize the order of C, then calculate what the overall false positive and negative rates would be as we include progressively more votes from the list. For each profile, we randomize the list and conduct the simulation 100 times, then average the rates for each number of votes. Intuitively, what this process reveals is how the accuracy of the turker group changes as we increase the number of votes, irrespective of the specific order that the votes arrive in.

The results of our simulations demonstrate that there are limits to how much accuracy can be improved by adding more turkers to the group, as shown in Figure 9. Each line plots the average accuracy over all Sybil and legitimate profiles for a given group of turkers. For false positives, the trend is very clear: after 4 votes, there are diminishing returns on additional votes. For false negatives, the trend is either flat (US turkers), or it grows slightly worse with more votes (China and India).

Filtering Inaccurate Turkers. Since adding more turkers does not significantly increase accuracy, we now investigate the opposite approach: eliminating turkers that are consistently inaccurate. Many deployed crowdsourcing systems already use this approach [22]. Turkers are first asked to complete a pre-screening test, and only those who perform sufficiently well are allowed to work on the actual job.

In our scenario, turkers could be pre-screened by asking them to classify accounts from our ground-truth datasets. Only those that correctly classify x accounts, where x is some configurable threshold, would be permitted to work on actual jobs classifying suspicious accounts.

To gauge whether this approach improves Sybil detection accuracy, we conduct another simulation. We vary the accuracy threshold x, and at each level we select all turkers that have overall accuracy $\geq x$. We then plot the false negative rate of the selected turkers in Figure 10. Intuitively, this simulates turkers taking two surveys: one to pre-screen them for high accuracy, and a second where they classify unknown, suspicious accounts.

Figure 10 demonstrates that the false negative rate of the turker group can be reduced to the same level as experts by eliminating inaccurate turkers. The false negative rates are stable until the threshold grows $>40\%$ because, as shown in Figure 4, almost all the turkers have accuracy $>40\%$. By 70% threshold, all three test groups have false negative rates $\leq 10\%$, which is on par with experts. We do not increase the threshold beyond 70% because it leaves too few turkers to cover all the Sybil profiles in our dataset. At the 70% threshold, there are 156 Chinese, 137 Indian, and 223 US turkers available for work.

5.4 Profile Difficulty

The last question we examine in this section is the following: are there extremely difficult "stealth" Sybils that resist classification by both turkers and experts? As we show in Table 3, neither experts nor turkers have 0% false negatives when classifying Sybils. What is unknown is if there is correlation between the false negatives of the two groups.

To answer this question, we plot Figure 11. Each scatter plot shows the average classification accuracy of the Sybils from a particular region. The x-axes are presented in ascending order by turker accuracy. This is why the points for the turkers in each subfigure appear to form a line.

Figure 11 reveals that, in general, experts can correctly classify the vast majority of Sybils that turkers cannot (*e.g.* turker accuracy $<50\%$). There are a select few, extremely difficult Sybils that evade both the turkers and experts. These "stealth" Sybils represent the pinnacle of difficulty, and blur the line between real and fake user profiles. There is only one case, shown in Figure 11(a), where turkers correctly identify a Sybil that the experts missed.

One important takeaway from Figure 11 is that "stealth" Sybils are a very rare phenomenon. Even if a crowdsourced Sybil detector was unable to identify the them, the overall detection accuracy is so high that most Sybils will be caught and banned. This attrition will drive up costs for attackers, deterring future Sybil attacks.

Turker Accuracy and Luck. Another takeaway from Figure 11 is that some profiles are difficult for turkers to classify. This leads to a new question: are the most accurate turkers actually better workers, or were they just lucky during the survey? Hypothetically, if a turker was randomly shown all "easy" Sybils, then they would appear to be accurate, when in fact they were just lucky.

Close examination of our survey results reveals that accurate turkers were not lucky. The 75 Chinese turkers who

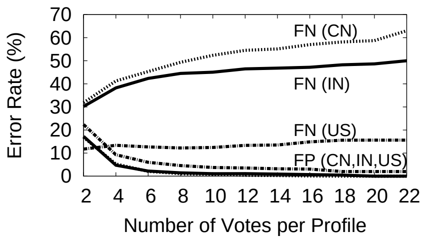


Figure 9. Votes per profile versus the FP and FN rate.

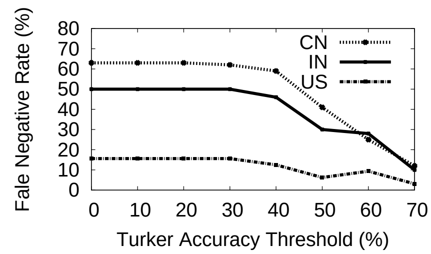
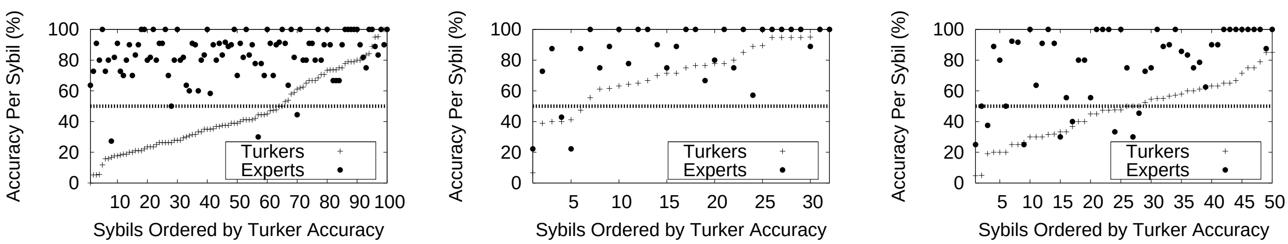


Figure 10. Accuracy threshold versus the false negatives.



(a) Renren (b) Facebook US (c) Facebook India

Figure 11. Scatter plots of average accuracy per Sybil profile.

achieved ≥90% accuracy were collectively shown 97% of Renren Sybils during the survey. Similarly, the 124 US turkers with ≥90% accuracy were also shown 97% of the Facebook US Sybils. Thus, the high accuracy turkers exhibit almost complete coverage of the Sybils in our dataset, not just the "easy" ones.

6 A Practical System

In this section, we design a crowdsourced Sybil detection system based on the lessons learned from our experiments. We focus on practical issues such as scalability, accuracy, and privacy. We first describe our system architecture that enables crowdsourced Sybil detection at large scale. Second, we use trace-driven simulations to examine the tradeoff between accuracy and cost in such a system. Finally, we discuss how to preserve user privacy when distributing user profile data to turkers.

6.1 System Design and Scalability

The first challenge we address is scalability. Today's social networks include hundreds of millions of users, most of whom are legitimate. How do we build a system that can focus the efforts of turkers on the subset of accounts that are suspicious? To address this challenge, we propose a hierarchical Sybil detection system that leverages both automated techniques and crowdsourced human intelligence. As shown in Figure 12, the system contains two main layers: the *filtering layer* and the *crowdsourcing layer*.

Filtering Layer. In the first layer, we use an ensemble of filters to locate suspicious profiles in the social network. These filters can be automated using techniques from prior work, such as Sybil community detection [3] and feature based selection [31]. Filters can also be based on existing "user report" systems that allow OSN users to "report" or "flag" suspicious profiles. These tools are already implemented in social networks such as Facebook and Renren, and help to dramatically reduce the number of target profiles studied by our crowdsourcing layer.

Crowdsourcing Layer. The output of the filtering layer is a set of suspicious profiles that require further validation (Figure 12). These profiles are taken as input by the crowdsourcing layer, where a group of turkers classify them as legitimate or fake. OSNs can take further action by either banning fake accounts, or using additional CAPTCHAs to limit potentially damaging behavior.

We begin with two techniques to increase the accuracy of the turker group. First, we use majority voting by a group of workers to classify each suspicious profile. Our earlier results in Table 3 show that the accuracy of the crowd is significantly better than the accuracy of individual turkers.

The second mechanism is a "turker selection" module that filters out inaccurate turkers. Figure 10 shows that eliminating inaccurate turkers drastically reduces the false negative rate. As shown in Figure 12, we can implement turker selection by randomly mixing in "ground-truth profiles" that have been verified by social network exployees with the larger set of suspicious profiles. By examining a

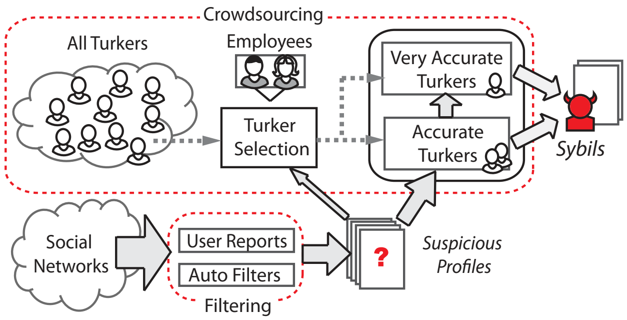


Figure 12. Crowdsourced Sybil detector.

tester's answers on the ground-truth profiles, we can gauge the evaluation accuracy of each worker. This accuracy test is performed continuously over time, so that any significant deviation in the quality of turker's work will be detected. This protects against malicious attackers who go "undercover" as one of our testers, only to turn malicious and generate bad results when presented with real test profiles.

6.2 System Simulations and Accuracy

In this section, we examine the tradeoff between accuracy and cost in our system. The overall goal of the system is to minimize false positives and negatives, while also minimizing the number of votes needed per profile (since each vote from a turker costs money). There is a clear tradeoff between these two goals: as shown in Figure 9, more votes reduces false positives.

Simulation Methodology. We use trace-driven simulations to examine these tradeoffs. We simulate 2000 suspicious profiles (1000 Sybil, 1000 legitimate) that need to be evaluated. We vary the number of votes per profile, V, and calculate the false positive and false negative rates of the system. Thus, each profile is evaluated by V random turkers, and each turker's probability of being correct is based on their results from our user study. In keeping with our system design, all turkers with <60% accuracy are eliminated before the simulation by our "turker selection" module.

We consider two different ways to organize turkers in our simulations. The first is simple: all turkers are grouped together. We refer to this as *one-layer* organization. We also consider *two-layer* organization: turkers are divided into two groups, based on an accuracy threshold T. Turkers with accuracy $> T$ are placed in the *upper layer*, otherwise they go into the *lower layer*.

In the two-layer scheme, profiles are first evaluated by turkers in the lower layer. If there is strong consensus among the lower layer that the profile is Sybil or legitimate, then the classification stands. However, if the profile is *controversial*, then it is sent to the more accurate, upper layer turkers for reevaluation. Each profile receives B votes in the lower layer and U votes in the upper layer. Intuitively,

Threshold	70%	80%	90%
L (Lower Layer, Accurate Turkers)	5	5	5
U (Upper Layer, Very Accurate Turkers)	3	3	2

Table 5. Optimal # of votes per profile in each layer in order to keep the false positives <1%.

the two-layer system tries to maximize the utility of the very accurate turkers by only having them evaluate difficult profiles. Figure 12 depicts the two-layer version of our system.

In our design, we cap the maximum acceptable false positive rate at 1%. Our motivation is obvious: social network providers will not deploy a security system that has a non-negligible negative impact on legitimate users. We conducted simulations on all our turker groups, with consistent results across groups. For brevity, we limit our discussion here to results for the Chinese turkers. As shown in Figure 6, the Chinese turkers have the worst overall accuracy of our turker groups. Thus, they represent the worst-case scenario for our system. The US and Indian groups both exhibit better performance in terms of cost and accuracy during simulations of our system.

Votes per Profile. In the one-layer simulations, the only variable is votes per profile V. Given our constraint on false positives $<1\%$, we use multiple simulations to compute the minimum value of V. The simulations reveal that the minimum number of votes for the Chinese profiles is 3; we use this value in the remainder of our analysis.

Calculating the votes per profile in the two-layer case is more complicated, but still tractable. The two-layer scenario includes four variables: votes per profile (U upper and L lower), the accuracy threshold between the layers T, and the controversial range R in which profiles are forwarded from the lower to upper layer. To calculate L and U we use the same methodology as in Figure 9. Turkers are divided into upper and lower layers for a given threshold $T \in [70\%, 90\%]$, then we incrementally increase the votes per profile in each layer until the false positive rate is $<1\%$. The false positive rate of each layer is independent (*i.e.* the number of votes in the lower layer does not impact votes in the upper layer), which simplifies the calculations. The controversial range only effects the false negative rate, and is ignored from these calculations.

Table 5 shows the minimum number of votes per profile needed in the upper and lower layers as T is varied. We use these values in the remainder of our analysis.

Figure 13 shows the average votes per profile in our simulations. Three of the lines represent two-layer simulations with different R values. For example, $R = [0.2, 0.9]$ means that if between 20% and 90% of the turkers classify the profile as a Sybil, then the profile is considered controversial. Although we simulated many R ranges, only three repre-

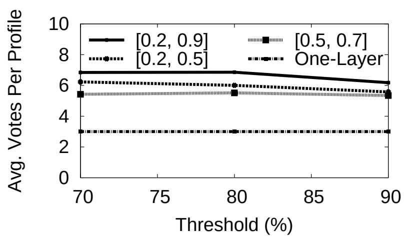


Figure 13. Threshold versus average votes per profiles.

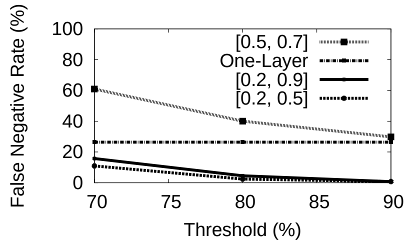


Figure 14. Threshold versus false negative rate.

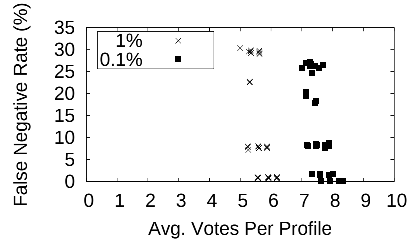


Figure 15. Tradeoff between votes per profile and desired accuracy.

sentative ranges are shown for clarity. The number of votes for the one-layer scheme is also shown.

The results in Figure 13 show that the number of votes needed in the various two-layer scenarios are relatively stable. As R varies, the number of profiles that must be evaluated by *both* layers changes. Thus, average votes per profile fluctuates, although the average is always $\leq L + U$ from Table 5. Overall, these fluctuations are minor, with average votes only changing by $\approx$1.

False Negatives. Judging by the results in Figure 13, the one-layer scheme appears best because it requires the fewest votes per profile (and is thus less costly). However, there is a significant tradeoff for lowering the cost of the system: more false negatives.

Figure 14 shows the false negative rates for our simulations. The results for the two-layer scheme are superior: for certain values of R and thresholds $\geq$80%, two-layers can achieve false negative rates $<$10%. The parameters that yield the lowest false negatives (0.7%) and the fewest average votes per profile (6) are $R = [0.2, 0.5]$ and $T = 90\%$. We use these parameters for the remainder of our analysis.

The results in Figures 13 and 14 capture the power of our crowdsourced Sybil detection system. Using only an average of 6 votes per profile, the system products results with false positive and negative rates both below 1%.

Reducing False Positives. In some situations, a social network may want to achieve a false positive rate significantly lower than 1%. In order to evaluate how much this change would affect costs, we re-ran all our simulations with the target false positive rate set to $<$0.1%. Figure 15 plots the number of votes per profile versus false negatives as the target false positive rate is varied. Each point in the scatter is a different combination of R and T values. The conclusion from Figure 15 is straightforward: to get $<$0.1% false positives, you need two additional votes per turker. This tradeoff is fairly reasonable: costs increase 33%, but false positives reduce by an order of magnitude.

Parameterization. Since our system parameters were optimized using actual user test results, they may not be ideal for every system or user population. The key takeaway is that given a user population, the system can be calibrated to provide high accuracy and scalability. We do not have sufficient data to make conjectures about how often or when systems require re-calibration, but it is likely that a deployed system might periodically recalibrate parameters such as V and T for continued accuracy.

6.3 The Costs of a Turker Workforce

Using the parameters derived in the previous section, we can estimate how many turkers would be needed to deploy our system. Using the parameters for Renren, each profile requires 6 votes on average, and turkers can evaluate one profile every 20 seconds (see Figure 8). Thus, a turker working a standard 8-hour day (or several turkers working an equivalent amount of time) can examine 1440 profiles.

Data from a real OSN indicates that the number of turkers needed for our system is reasonable. According to [3], Tuenti, a Spanish online social network, has a user-base of 11 million and averages 12,000 user reports per day. Our system would require 50 full-time turkers to handle this load. If we scale the population size and reports per day up by a factor of 10, we can estimate the load for a large OSN like Facebook. In this case, our system requires 500 turkers. Our own experience showed that recruiting this many turkers is not difficult (Table 1). In fact, following our crowdsourcing experiments on this and other projects [30], we received numerous messages from crowd requesting more tasks to perform.

Finally, we estimate the monetary cost of our system. Facebook pays turkers from oDesk \$1 per hour to moderate images [10]. If we assume the same cost per hour per turker for our system, then the daily cost for deployment on Tuenti (*i.e.* 12,000 reports per day) would only be \$400. This compares favorably with Tuenti's existing practices: Tuenti pays 14 full-time employees to moderate content [3]. The estimated annual salary for Tuenti employees are roughly €30,000[3], which is about $20 per hour. So the Tuenti's moderation cost is $2240 per day, which is significantly more than the estimated costs of our turker workforce.

6.4 Privacy

Protecting user privacy is a challenge for crowdsourced Sybil detection. How do you let turkers evaluate user profiles without violating the privacy of those users? This issue does not impact our experiments, since all profiles are from public accounts. However, in a real deployment, the system needs to handle users with strict privacy settings.

One possible solution is to only show turkers the public portions of users' profiles. However, this approach is problematic because Sybils could hinder the detection system by setting their profiles to private. Setting the profile to private may make it more difficult for Sybils to friend other users, but it also cripples the discriminatory abilities of turkers.

A better solution to the privacy problem is to leverage the OSNs existing "report" filter. Suppose Alice reports Bob's profile as malicious. The turker would be shown Bob's profile *as it appears to Alice*. Intuitively, this gives the turker access to the same information that Alice used to make her determination. If Alice and Bob are friends, then the turker would also be able to access friend-only information. On the other hand, if Alice and Bob are strangers, then the turker would only have access to Bob's public information. This scheme prevents users from abusing the report system to leak the information of random strangers.

7 Related Work

The success of crowdsourcing platforms on the web has generated a great deal of interest from researchers. Several studies have measured aspects of Amazon's Mechanical Turk, including worker demographics [12, 24] and task pricing [5, 11, 19]. There are studies that explore the pros and cons to use MTurk for user study [16].

Many studies address the problem of how to maximize accuracy from inherently unreliable turkers. The most common approach is to use majority voting [17, 25], although this scheme is vulnerable to collusion attacks by malicious turkers [26]. Another approach is to pre-screen turkers with a questionnaire to filter out less reliable workers [22]. Finally, [26] proposes using a tournament algorithm to determine the correct answer for difficult tasks.

In this study, we propose using crowdsourcing to solve a challenging OSN security problem. However, many studies have demonstrated how crowdsourcing can be used by attackers for malicious ends. Studies have observed malicious HITs asking turkers to send social spam [30], perform search engine optimization (SEO) [21], write fake reviews [23], and even install malware on their systems [15].

8 Conclusion and Open Questions

Sybil accounts challenge the stability and security of today's online social networks. Despite significant efforts from researchers and industry, malicious users are creating increasingly realistic Sybil accounts that blend into the legitimate user population. To address the problem today, social networks rely on ad hoc solutions such as manual inspection by employees.

Our user study takes the first step towards the development of a scalable and accurate crowdsourced Sybil detection system. Our results show that by using experts to calibrate ground truth filters, we can eliminate low accuracy turkers, and also separate the most accurate turkers from the crowd. Simulations show that a hierarchical two-tiered system can both be accurate and scalable in terms of total costs.

Ground-truth. Our system evaluation is constrained by the ground-truth Sybils used in our user study, *i.e.* it is possible that there are additional Sybils that were not caught and included in our data. Thus, our results are a lower bound on detection accuracy. Sybils that can bypass Facebook or Renren's existing detection mechanisms could potentially be caught by our system.

Deployment. Effective deployment of crowdsourced Sybil detection mechanisms remains an open question. We envision that the crowdsourcing system will be used to complement existing techniques such as content-filtering and statistical models. For example, output from accurate turkers can teach automated tools which fields of the data can most easily identify fake accounts. Social networks can further lower the costs of running this system by utilizing their own users as crowdworkers. The social network can replace monetary payments with in-system virtual currency, *e.g.* Facebook Credits, Zynga Cash, or Renren Beans. We are currently discussing internal testing and deployment possibilities with collaborators at Renren and LinkedIn.

Countermeasures. An effective solution must take into account possible countermeasures by attackers. For example, ground-truth profiles must be randomly mixed with test profiles in order to detect malicious turkers that attempt to poison the system by submitting intentionally inaccurate results. The ground-truth profiles must be refreshed periodically to avoid detection. In addition, it is possible for attackers to infiltrate the system in order to learn how to improve fake profiles to avoid detection. Dealing with these "undercover" attackers remains an open question.

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