Combating Friend Spam Using Social Rejections

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Abstract— **Unwanted friend requests in online social networks, also known as friend spam, have proven to be among the most evasive malicious activities. This is evident by the fact that most OSN users experience friend spam on a substantially more frequent basis than they experience spam on their newsfeeds or other types of unwanted traffic. Besides directly annoying users, friend spam can be used to undermine social-graph-based defense schemes, which effectively bind the number of accepted Sybils to the total number of social connections between Sybils and non-Sybil users. Hence, allowing malicious accounts to effortlessly solicit friend requests to unsuspected users who may accept them, can lead to the collapse of a major defense line.**

We propose Rejecto, a system that leverages social rejections to throttle friend spam. Rejecto stems from the observation that even well-maintained fake accounts inevitably receive a significant number of social rejections, namely they have their friend requests rejected or they are reported by users. Our key insight is to partition the social graph into two regions such that the aggregate acceptance rate of the friend requests from one region to the other is minimized. We argue that our design, which leverages the aforementioned graph cut, can reliably detect a region that comprises friend spammers. At the same time, it is resilient to the collusion and self-rejection evasion strategies. To efficiently obtain the graph cut, we extend the Kernighan-Lin heuristic and use it to iteratively detect and remove the accounts that send out friend spam. Through extensive simulations, we show that Rejecto can discern friend spammers under a broad range of scenarios and that it is resilient to strategic attackers.

I. Introduction

Unscrupulous users increasingly find Online Social Networking (OSN) platforms as lucrative targets for malicious activities, such as sending spam and spreading malware. The profitability of such activities and the fact that a large portion of the OSN communication takes place over symmetric social links (e.g., Facebook) motivate attackers to connect to real users. In particular, attackers leverage the open nature of OSNs and send to legitimate users unwanted friend requests, also known as *friend spam* [12], [32].

Friend spam can result in OSN links that do not correspond to social relationship among users, thus it enables the pollution of the underlying undirected social graph. Because OSN providers build on social graphs their core functionalities that often assume a social graph solely consists of links representing social trust of user pairs, the consequences of falsely accepted requests by unsuspected users are severe. In particular, the false OSN links resulting from friend spam can compromise the accuracy of social ad targeting [24], [34] and search [6], [10], and the privacy of shared content by users.

Moreover, friend spam can be used to undermine the effectiveness of defense systems that are either built upon [15], [19], [37] or take input signals [36] from social graphs. For example, the additional OSN links that fake accounts (called Sybils) obtain via friend spam can enable part of them to evade the detection of social-graph-based defense systems [15], [19], [37]. This is because these approaches bound the number of undetected fake accounts to the number of OSN links between Sybils and real users, e.g., $O(\log n)$ accounts per link [15], [37], where n is the total number of users.

Despite major advances in the suppression of malicious activities and accounts [12], friend spam appears to be more evasive than regular spam [7]. OSN users still experience friend spam on a frequent basis [3], [11]. One of the suggested remedies has been to restrict requests only to friends of friends. This, however, subtracts from the openness of the OSN.

OSNs such as Facebook employ specific "terms of use" to protect the genuineness of social edges: users are only allowed to send friend requests to people that they know in the real life. However, it is often hard for OSNs to determine if a friend request obeys their regulations. We therefore aim to answer the question: "how can we design a robust system to throttle friend spam in OSNs?" Such a system benefits OSNs in that it can substantially sterilize the social graph by stemming unwanted friend requests. This improves the effectiveness of social-graph-based detection mechanisms and the accuracy of social search and ad-targeting, and helps preserve user privacy.

Our hypothesis is that we can uncover the fake accounts (Sybils) that indiscriminately send out friend spam in symmetric OSNs (e.g., Facebook and LinkedIn) by leveraging the rejection of unwanted friend requests. The insight is that although some OSN users accept friend requests from unknown users, cautious users reject, ignore, or report them to the OSN providers. The attackers behind the spamming accounts usually have limited knowledge about the degree of their targets' security awareness, partly due to the massive scale of today's OSNs and their significant efforts in protecting the online privacy and safety of the users. As a result, the spamming accounts inevitably receive a significant number of *social rejections* from legitimate users. We confirmed this in our study on fake Facebook accounts in the wild (§II). In contrast, friend requests from legitimate users are only sporadically rejected because they are often sent to people the senders know [36].

We designed and implemented a system called *Rejecto*. It exploits the readily available social rejections in OSNs and systematically uncovers the fake accounts that act as friend spammers. Rejecto monitors the friend requests sent out by users and augments the social graph with directed social rejections. It signals an anomaly if it detects a group of users that have only a small fraction of their friend requests accepted by legitimate users. Once an OSN detects the fake accounts used for friend spam, it can prevent them from sending requests in the future. The goal of our system is to be able to effectively identify fractions of users that participate in friend spam with a high recall and very low false positives.

Although using social rejections to combat friend spam is intuitive, designing a robust scheme that is strategy-proof poses an algorithmic challenge. First, the spamming fake accounts can attempt to evade the detection by *collusion*. Specifically, they can accept each other's requests, decreasing the fraction of the rejected requests of each individual account to that of a legitimate user's. Second, a part of the fake accounts can mimic legitimate users by rejecting friend requests from other fake accounts. By doing so the attacker sacrifices his accounts that got the rejections. Yet, he whitewashes his rejecting accounts because they now reject requests in the same way legitimate users do. We call this strategy *self-rejection*.

Previous work [16], [35] took request rejections into account for fake account detection. Like Rejecto, they also rely on the premise that legitimate users reject a portion of unwanted friend requests. However, these designs [16], [35] did not fully utilize the power of social rejection and were not made resilient to the collusion and self-rejection attack strategies. Similarly, Machine Learning classifiers that use request rejections [36] are usually based on individual user features, thus they suffer from manipulation.

Rejecto systematically addresses the above challenges. To be resilient to collusion, we take spamming accounts as a group and only consider the requests sent outside of that group. To this end, it formulates the friend spammer detection as a graph partitioning algorithm (§IV-A). Specifically, while the portion of the accepted friend requests among legitimate accounts is high, the aggregate acceptance rate of all the requests sent from fake to legitimate accounts is substantially lower, regardless of the acceptance of the requests among the fake accounts. Therefore, Rejecto extends the Kernighan-Lin approach [25] and uses it to partition the social graph into two regions such that the aggregate acceptance rate of the requests from one region to the other is minimized. We then declare the accounts in the region with the minimum aggregate acceptance rate as suspicious. Because this aggregate acceptance rate is independent of the requests and links among fake accounts, an attacker cannot arbitrarily boost this rate by having his accounts befriend each other.

To mitigate the impact of the self-rejection attack strategy and cope with the existence of multiple independent groups of fake accounts, we apply the graph partitioning multiple times and iteratively identify fake-account groups after pruning the detected ones from the social graph (§IV-E). As a result, the additional rejections among fake accounts achieve nothing more than exposing the rejected accounts earlier to Rejecto's detection.

We implemented Rejecto on Spark [39], an efficient in-memory large-data processing platform. We evaluate Rejecto through extensive simulations (§VI) on real social graphs, and we show that it can withstand friend spam under a broad range of scenarios and that it is resilient to attack strategies.

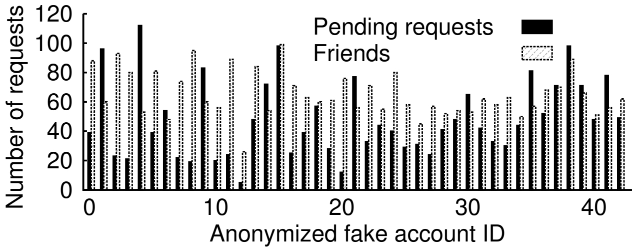


Fig. 1: The numbers of friends and pending requests on purchased accounts. These accounts have a significant fraction of pending requests.

As a demonstration of Rejecto's effectiveness on improving OSN-related services, we apply it to social-graph-based Sybil detection. Specifically, we run Rejecto over the rejection-augmented social graph and remove the detected friend spammers along with their social links. We then use a social-graph-based Sybil-detection approach to uncover the rest of the fake accounts, which usually have limited social connections to legitimate users as they do not send out friend spam. In this way, we obtain an effective in-depth defense against fake accounts (§II-C, §VI-D).

In summary, this work makes the following contributions:

- We formulate the detection of the fake accounts that act as friend spammers as a graph partitioning problem. To the best of our knowledge, this is the first formulation that makes a friend-spam detection system resilient to attack strategies.
- To efficiently partition a rejection-augmented social graph, we transform to a set of partitioning problems, each with a linear objective function, and we extend the Kernighan-Lin approach [25] to solve them.
- We have implemented a scalable prototype of Rejecto [4] that can process multimillion-user social graphs on an EC2 cluster. Our efficiency analysis indicates that the prototype can scale up to OSNs with hundreds of millions of users, provided that the aggregate memory of the cluster suffices.

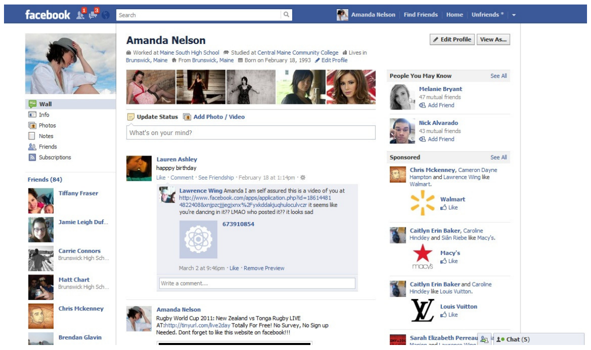
II. Motivation

We present a study of fake Facebook accounts we obtained from the underground market. This study reveals that social rejections are a natural byproduct of friend spam, and motivates us to use them to trace and defend against the spammers.

A. Social rejections by legitimate users

Legitimate users are substantially less affected if fake accounts are not connected to them. Thus, fake accounts are incentivized to obtain OSN links to real users. However, those that aggressively befriend legitimate users in symmetric OSNs trigger social rejections in the form of rejected, ignored, or reported as abusive friend requests. Since user reports are only accessible by OSN providers, we focus our study on the ignored and rejected friend requests.

Study of purchased Facebook accounts. We conducted a study of well-maintained fake Facebook accounts from the



Amanda Nelson

Worked at Maine South High School · Studied at Central Maine Community College · Lives in Brunswick, Maine · From Brunswick, Maine · Born on February 18, 1993 · Edit Profile

Lauren Ashley
happpy birthday
Like · Comment · See Friendship · February 18 at 1:14pm

Lawrence Wing Amanda I am self assured this is a video of you at http://www.facebook.com/apps/application.php?id=186144814822408&xnjpzcjjjegjxnx%2Fyxkddakjuqhuloculvczr it seems like you're dancing in it?? LMAO who posted it?? it looks sad
673910854
March 2 at 9:46pm · Like · Remove Preview

Amanda Nelson
Rugby World Cup 2011: New Zealand vs Tonga Rugby LIVE AT:http://tinyurl.com/live2day Totally For Free! No Survey, No Sign up Needed. Dont forget to like this website on facebook!!!

Chris Mckenney, Cameron Dayne Hampton and Lawrence Wing like Walmart.

Caitlyn Erin Baker, Caroline Hinckley and Siân Riebe like Macy's.

Caitlyn Erin Baker and Caroline Hinckley like Louis Vuitton.

Fig. 2: A sample profile of our purchased accounts.

underground market [1], [2] to understand the social rejections in the real world. We purchased fake Facebook accounts from workers on Freelancer [2] for this study. Because our purchases solely played the role of collecting fake accounts that are for sale and nevertheless available in the underground market, the Duke University Institutional Review Board (IRB) informed us that this study does not require a formal approval process. The fake accounts in the underground market are priced according to their lifetime, the number of friends, the number of profile pictures, and other factors. To investigate the trace of social rejections on live fake accounts, we explicitly required that each of the fake accounts we purchase should have “>50 real US friends”. In this study, we use 43 purchased accounts, each of which is at least one year old. They are purchased at different vendors, and in total have 2804 friends and 2065 pending requests, as shown in Figure 1. Figure 2 shows the profile of a sample account. The profile is crafted as a college student with pictures, and with posts on the wall. This account has 84 friends and has interacted with some friends, as indicated by the records of messages and comments.

The number of friends our purchased accounts have on Facebook is only an upper bound on the number of real users that they successfully befriended. This is because part of the delivered Facebook friends on purchased fake accounts may be also fake, although we required real-user friends when we placed our orders. To this end, we studied the associated attributes of the friends on our purchased accounts. Figure 3 shows the CDF of the friends with respect to their degrees in the social graph. We can see that some of the friends have a social degree >1000 each, indicating that they are either careless Facebook users or abusive fake accounts. Figure 4 and Figure 5 shows the CDFs of the friends with respect to the posts on their walls and the photos they have uploaded. A large portion of the friend users on our purchased accounts are quite active, as they have posted on walls and uploaded photos, and they got comments and likes from their friends. Again, we cannot determine if the friends of a friend are fake or not. However, we do observe a part of the friends of our purchased accounts form full-mesh communities, which might indicate that they can be fake.

Fake accounts receive rejections. We examine the pending friend requests from each purchased account. Facebook does not provide this statistic to users directly, but provides APIs to access the pending friend requests. Figure 1 shows the numbers of friends and pending requests on each account. Although these well-maintained accounts have many OSN links and sufficiently completed profiles, we can see that they all have a significant number of pending requests. Specifically, the fraction of pending requests of each user ranges from 16.7% to 67.9%. This indicates that legitimate OSN users tend to reject requests from unknown and possibly fake users. Therefore, the fake accounts inevitably receive social rejections, during the process of soliciting a number of legitimate user friends. In addition, a recent study on RenRen [36] also reported excessive rejections on fake accounts, but focusing on those that had been caught.

B. *Rationale of using social rejections*

We leverage the social rejections to uncover fake accounts that send out unwanted friend requests.

Non-manipulability of social rejection towards innocent users. In a symmetric OSN, a social rejection is a reliable signal, which is guarded by a feedback loop between two different users, the sender and the receiver. A user is able to signal a social rejection only if she received an unwanted friend request. That is, a legitimate user rarely receives any social rejections if she never sends out spam requests. Therefore, a group of malicious users cannot collude to give an arbitrary number of social rejections to another group of victims who never sent to them friend spam. If such manipulation was effective, it would discredit the defense scheme. This is in contrast to the negative ratings in other online services such as YouTube, where users are allowed to rate arbitrarily.

Machine-learning classifiers are insufficient. The social rejections can be used to directly detect fake accounts with machine-learning (ML) techniques. However, ML-based techniques [36] require extensive calibration efforts due to the abundance of possible legitimate and malicious behaviors in OSNs. Besides, these approaches are usually based on individual user features, and can be vulnerable to strategic attacks [9].

C. *Defense in depth with social-graph-based approaches*

A further motivation of our work is to build an in-depth defense against Sybil attacks in OSNs that combines Rejecto with existing social-graph-based approaches. These existing schemes uncover clusters of OSN fake accounts that have a limited number of links to real users [15], [19], [37]. Meanwhile, Rejecto prevents fake accounts from obtaining a large number of OSN links by detecting those friend spammers. Thus, they can constitute a defense in depth. After effectively blocking friend spammers and pruning their OSN links from the graph, a large portion of the clusters of fake accounts with a limited number of OSN links to real users can be uncovered by traditional social-graph-based approaches. We use OSN Sybil defense as a demonstration of Rejecto's effectiveness on improving existing OSN functionality (§VI-D).

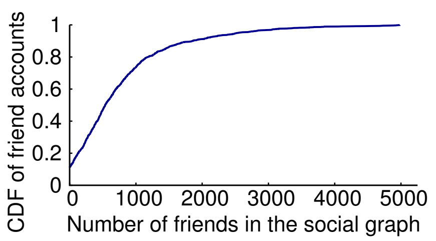


Fig. 3: **CDF of the friend accounts of our purchased accounts, with respect to their degrees on the social graph.**

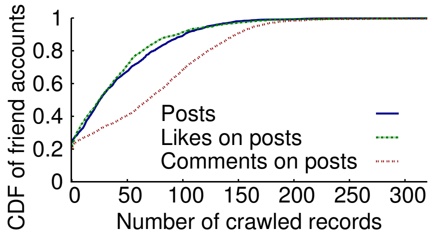


Fig. 4: **CDFs of the friend accounts of our purchased accounts, with respect to the number of posts, and to the numbers of the comments and likes on the posts, respectively.**

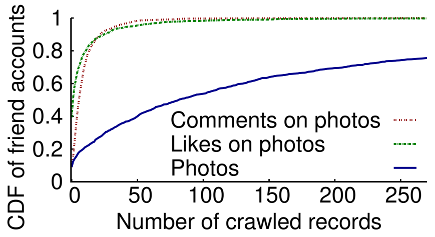


Fig. 5: **CDFs of the friend accounts of our purchased accounts, with respect to the number of photos, and to the numbers of the comments and likes on the photos, respectively.**

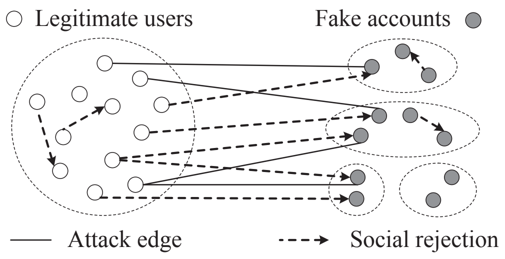


Fig. 6: **Legitimate users, fake accounts, and social rejections in an OSN under friend spam. Fake accounts can form distinct groups. The aggregate acceptance rate of requests from a group of friend spammers to legitimate users is low. A fake-account group may choose not to send out friend spam.**

III. Models, Assumptions, and Goals

In this section, we introduce our system model, threat model, assumptions, and goals.

A. Models

System model. We augment the social graph with directed social rejections, which we call an *augmented social graph*. We model this graph as $G = (V, F, \vec{R})$, where V is the user set in an OSN, F represents the OSN links among users $\{(u, v)\}$, and $\vec{R}$ represents the social rejections $\{\langle u, v\rangle\}$. We consider OSN links bidirectional whose establishment requires mutual agreement as in the real world. The social rejections are directional: a rejection edge $\langle u, v\rangle$ represents a rejection of user v's request by user u or a report by user u that flags v's request as abusive. A user u may give multiple social rejections to another user v over time. For simplicity, we denote them as a single rejection edge. As in previous work [15], [19], [37], [38], we refer to the OSN links that straddle the boundary between fake accounts and legitimate users as *attack edges* (Figure 6).

The user set V consists of two disjoint parts: a) L: the subset of legitimate users, and b) M: the subset of fake accounts controlled by attackers, where $V = L \cup M$. For any two disjoint user subsets X and Y ($X \cap Y = \emptyset$), where Y can be $\bar{X}$ ($\bar{X} = V - X$), we define the following:

Group friendship set $F(X, Y)$**:** the set of friendships each of which connects a user in X with another user in Y. $F(X, Y) = \{(u, v)|u \in X, v \in Y\}$. $F(X, Y) = F(Y, X)$ due to the reciprocation of social connection.

Group rejection set $\vec{R}\langle X, Y\rangle$**:** the set of rejections casted by users in X to users in Y. $\vec{R}\langle X, Y\rangle = \{\langle u, v\rangle | u \in X, v \in Y\}$. Because the rejections are directed, it is unnecessary that $\vec{R}\langle X, Y\rangle$ equal to $\vec{R}\langle Y, X\rangle$.

Aggregate acceptance rate $\vec{AC}\langle X, Y\rangle$**:** the aggregate acceptance rate of the friend requests from X to Y. $\vec{AC}\langle X, Y\rangle = \frac{|F(Y,X)|}{|F(Y,X)|+|\vec{R}\langle Y,X\rangle|}$. This rate only considers the OSN links and rejections across the user sets.

Threat model. An OSN connects users on a social graph. Shared content and interaction among users flows over the social connections. Fake accounts send out friend spam in the hope of gaining additional OSN links to legitimate users. Meanwhile, they may seek to hide themselves or even disguise as legitimate users. We consider two attack strategies which we believe form the basis of the spectrum of various attacks: *collusion* and *self-rejection*. In a collusion attack, fake accounts arbitrarily improve the acceptance rate of the requests of each individual by sending and accepting requests among themselves. Using the self-rejection strategy, fake accounts mimic legitimate users by rejecting requests from others. Although fake accounts cannot manipulate the requests from legitimate users, they can choose to reject requests from themselves and whitewash the rejecting accounts. Note that attackers cannot manipulate the rejections to legitimate users who can choose not to send requests to controlled accounts.

B. Assumptions

We make the following assumptions:

Low aggregate acceptance rate of the requests from fake accounts to legitimate users. We assume that legitimate users rarely accept all unwanted friend requests. As a result, the aggregate acceptance rate of the attackers' requests to legitimate users is low. This is in contrast to the acceptance rate of legitimate users, whose requests are only sporadically rejected. This is because in symmetric OSN's such as Facebook legitimate users usually send requests to users they know.

Known legitimate users and spamming users. We assume that OSN providers have prior knowledge of a small number of legitimate users and friend-spamming users. This prior knowledge can be obtained by manually inspecting a set of random users [15]. We refer to those known users as *legitimate* and *spammer* seeds, respectively. We leverage these known seeds to further improve the accuracy of our system (§ IV-F).

C. Goals

Our aim is to use social rejection to defend against the fake accounts that send out friend spam. We have two main goals:

Accuracy. Rejecto should be able to identify the fake accounts that send out unwanted requests to legitimate users but do not get a large portion accepted, irrespective of the request acceptance among the fake accounts. Rejecto must remain effective even under various strategic attacks. Meanwhile, Rejecto should not flag legitimate users with sporadic rejections.

Efficiency. Today's OSNs serve billions of users. Our system should be able to efficiently detect friend spammers and enable large OSNs to protect their services and users.

IV. System design

We now describe the design of Rejecto. We first provide an overview of the approach.

A. Overview

Rejecto is based on the observation that fake accounts sending out friend spam inevitably receive a significant number of social rejections from the OSN users they attempt to connect to. As a result, the excessive social rejections lead to a low aggregate acceptance rate of the friend requests from fake to legitimate accounts.

Our key insight is that the low aggregate acceptance rate of the spam requests can enable us to reliably differentiate the spammers from other users. Meanwhile, we build into Rejecto's design the resilience to strategic befriending behavior by spammers. In order to be resistant to collusion attacks, Rejecto augments the social graph with directed rejections and formulates the detection of friend spammers as the problem of partitioning an augmented social graph into two regions, such that the aggregate acceptance rate of the requests from one region to the other is minimized. We reduce to this detection problem from the minimum ratio cut in multi-commodity flow [13], [27], which is known to be NP-hard [22]. We extend a widely-used optimization heuristic, the Kernighan-Lin (KL) algorithm [25], and use it to accurately uncover the fake accounts used for friend spam. To cope with disjoint fake-account groups and the fake accounts mimicking real users by rejecting other Sybils, our system applies KL over multiple rounds, and iteratively identifies groups of friend spammers and their associated links and rejections in the social graph.

By detecting friend spammers and removing the OSN links yielded by friend spam, Rejecto can sterilize the social graph upon which many OSN functionalities rely. In particular, after pruning the attack edges of friend spammers, Rejecto can substantially strengthen social-graph-based Sybil defenses, constituting a significant component of an in-depth Sybil defense system (§II-C).

B. The hardness of the problem

Because the aggregate acceptance rate of the friend requests from a fake-account group to legitimate users is low, we formulate the spammer/legitimate cut as the *minimum aggregate acceptance rate* (MAAR) cut in the augmented social graph. Suppose M' ($M' \subseteq M$) is the group of fake accounts whose requests yield the lowest acceptance rate, we have

$$\frac{|F(\bar{M'}, M')|}{|F(\bar{M'}, M')| + |\vec{R}\langle \bar{M'}, M' \rangle|} \leq \frac{|F(\bar{X}, X)|}{|F(\bar{X}, X)| + |\vec{R}\langle \bar{X}, X \rangle|},$$

that is, $\vec{AC}\langle M', \bar{M'} \rangle \leq \vec{AC}\langle X, \bar{X} \rangle$, for every $X \subset V$. By solving this MAAR problem, we identify the fake-account group M'. To uncover all friend spammers, we iteratively identify groups of fake accounts by repeatedly solving the MAAR problem and pruning the identified groups from the graph (§IV-E).

Strategic attackers can craft a cut with even lower aggregate acceptance rate within the fake account region. We handle those cases in §IV-E.

The MAAR problem is closely related to the MIN-RATIO-CUT problem [22]. By constructing a linear cost reduction from the MIN-RATIO-CUT problem, we show that it is NP-hard to find a MAAR cut in a social graph.

A primer on the MIN-RATIO-CUT problem. The MIN-RATIO-CUT problem is defined in the context of multi-commodity flow. Let $G = (V, E, c)$ be an undirected graph, where each edge e ($e \in E$) has a non-negative capacity $c(e)$. There is a set of k commodities $\{\vec{K}_1, \vec{K}_2, \ldots, \vec{K}_k\}$. Each commodity $\vec{K}_i$ is defined by a tuple $\vec{K}_i = \langle s_i, t_i, d_i \rangle$ ($s_i, t_i \in V$), where s_i and t_i are the *source* and the *sink*, and d_i is a positive *demand*. Given a cut $C = (U, \bar{U})$ such that $U \cup \bar{U} = V$ and $U \cap \bar{U} = \emptyset$, the *capacity* of the cut is the sum of the capacities of the cross-partition edges. The *cut ratio* is the capacity of C divided by the sum of demands of the cross-partition commodities. Therefore, the min ratio cut is a cut $C' = (U', \bar{U'})$ that minimizes:

$$O_{\text{MR}}(U) = \frac{\sum_{e \in E \cap (U, \bar{U})} c(e)}{\sum_{\langle s_i, t_i \rangle \in \langle U, \bar{U} \rangle \cup \langle \bar{U}, U \rangle} d_i}$$

Accordingly, the ratio of cut C' is called the *minimum cut ratio*. The MIN-RATIO-CUT problem is NP-hard [22].

Reduction from the 2-approximation MIN-RATIO-CUT problem. To detect friend spammers, we search for a partition of the user set $C^* = \langle U^*, \bar{U}^* \rangle$ with the minimum aggregate acceptance rate of the friend requests from U^* to $\bar{U}^*$.

$$U^* = \arg\min_{U \subset V} \frac{|F(\bar{U}, U)|}{|F(\bar{U}, U)| + |\vec{R}\langle \bar{U}, U \rangle|}$$

Minimizing the aggregate acceptance rate is equivalent to minimizing the aggregate friends-to-rejections ratio $\frac{|F(\bar{U}, U)|}{|\vec{R}\langle \bar{U}, U \rangle|}$, which we denote as $O_{\text{MAAR}}(U)$. We then reduce to our friend spammer detection problem from the 2-approximation MIN-RATIO-CUT problem, in which the edge capacities and the commodity demands are constants.

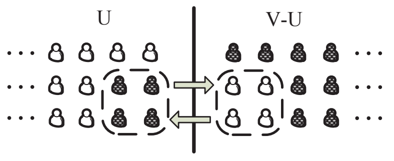


Fig. 7: An illustration of the Kernighan-Lin algorithm that improves a partition by interchanging misplaced nodes.

Suppose we have a MIN-RATIO-CUT instance $G = (V, E, c)$ with commodities $\{\vec{K}_1, \vec{K}_2, \ldots, \vec{K}_k\}$, where the capacity of an edge and the demand of a commodity are the same constant. We construct a corresponding MAAR instance in a social network $(V, F, \vec{R})$, where $F = E$ and $\vec{R} = \{\vec{K}_1, \vec{K}_2, \ldots, \vec{K}_k\}$. The MIN-RATIO-CUT instance is slightly different from the MAAR instance, in that the former counts the commodities in both directions across partitions, whereas MAAR considers only the rejections from legitimate users to Sybils. We now show that the optimal value of the MAAR instance is within a factor of two of that of the MIN-RATIO-CUT instance.

We compare the objectives of these two instances. We have $O_{\mathrm{MR}}(U) = \frac{|F(\bar{U},U)|}{|\vec{R}\langle U,\bar{U}\rangle|+|\vec{R}\langle \bar{U},U\rangle|}$ and $O_{\mathrm{MAAR}}(U) = \frac{|F(\bar{U},U)|}{|\vec{R}\langle \bar{U},U\rangle|}$. For any cut $C = (U, \bar{U})$, let U be the partition that has the larger number of incoming rejections, i.e., $|\vec{R}\langle \bar{U}, U\rangle| \geq \frac{1}{2}(|\vec{R}\langle U, \bar{U}\rangle| + |\vec{R}\langle \bar{U}, U\rangle|)$. Then $O_{\mathrm{MAAR}}(U) \leq 2O_{\mathrm{MR}}(U)$ holds. As a result, after traversing all possible cuts, we have $\min\{O_{\mathrm{MAAR}}\} \leq 2\min\{O_{\mathrm{MR}}\}$ (by contradiction). This indicates that the optimal value of the MAAR instance is larger than that of the MIN-RATIO-CUT, but at most twice as large.

Therefore, the optimal value of the MAAR problem is always within a factor of two of the ratio of the MIN-RATIO-CUT. Meanwhile, the MIN-RATIO-CUT problem is known to be NP-hard. The best existing MIN-RATIO-CUT algorithms achieve only an approximation factor of $O(\log |V|)$ [30]. It is widely believed this problem does not have a constant factor approximation unless P = NP.

C. The Kernighan-Lin algorithm

We use the Kernighan-Lin (KL) approach [25], one of the most effective heuristic algorithms for graph bisection. KL bipartitions an undirected graph into balanced parts, while minimizing the number of edges across parts. In particular, on an undirected graph $G = (V, E)$ KL seeks an approximation of the optimal cut $C = (U, \bar{U})$, such that $|U|/|V| \simeq r$ ($0 < r < 1$) and $|\{(u, v)|(u, v) \in E \cap (U \times \bar{U})\}|$ is minimized.

KL is a local optimization heuristic. It is based on the observation that one can always obtain the desired partition from an initial one by interchanging a particular subset of nodes from each part. Figure 7 illustrates that a partition can be refined by switching the misplaced nodes.

KL improves the partition quality by iteratively interchanging node sets. Within each iteration, it interchanges a pair of node sets that are sequentially selected in a greedy fashion according to the reduction of cross-part edges. This reduction is called *gain*. Specifically, the selection of node sets to be interchanged consists of two steps. First, it sequentially identifies a series of node-pair interchange operations each of which yields the largest gain if its predecessors are applied. That is, at each time it greedily picks up the node pair that yields the most reduction of cross-part edges and stores this node-pair interchange operation. Nodes involved in an identified interchange operation are not considered for another interchange any more during the same iteration. In this series, each subsequence starting from the beginning (prefix) indicates a candidate pair of interchanging node sets, as sequentially performing the interchanges of this subsequence can reduce the number of cross-part edges. Second, KL finds the interchange prefix that leads to the highest cumulative reduction of cross-part edges. It swaps the pair of node sets specified by the selected interchange prefix, generating an improved partition. Note that in order to avoid the local minimal KL executes the best node-pair interchange even if that leads to increment of the cross-part edges. KL then initiates the next iteration with this new partition it has obtained. This procedure repeats until no improvement can be made.

To enable efficient lookup for the node with the largest gain during the optimization, Fudiccia et al. [21] improved KL with the use of an array of linked lists, called a *bucket list*, which indexes each node according to its potential gain on the cross-part edge reduction. Specifically, a bucket list maps a node's gain to the index of a linked list. It puts nodes into the same linked list if each of them brings the same potential gain on the cross-part edge reduction after its switch to the other part. This enables us to find the node with the largest potential gain within constant time. In practice, since KL only requires a very small number of iterations, this improvement results in an $O(|V|)$ algorithm [21].

Alternative techniques. There are off-the-shelf approximation algorithms [30] for the MIN-RATIO-CUT problem, with an approximation factor of $O(\log |V|)$. We do not adopt them for large OSNs due to two shortcomings we perceived empirically: a) the approximation factor $O(\log |V|)$ of the cut ratio is not sufficient, which may cause substantial deviation from the optimal partitioning; b) the complexity of the algorithms indicates that it can be difficult for them to handle graphs with millions or billions of nodes. These algorithms [30] have a complexity of $\tilde{O}(|V|^2)$, where the $\tilde{O}(\cdot)$ notation suppresses poly-logarithmic factors. In addition, they do not have parallel implementation, making them hard to scale to today's OSNs whose social graphs usually cannot fit into the memory of a single machine.

D. Extending KL to rejection-augmented social graphs

Rejecto aims to find a partition of the entire user set $C^* = \langle U^*, \bar{U}^*\rangle$ that minimizes the friends-to-rejections ratio $\frac{|F(\bar{U},U)|}{|\vec{R}\langle \bar{U},U\rangle|}$. We cannot directly apply KL to our rejection-augmented social graph, because KL is designed to minimize the cross-region edges in an undirected graph, rather than the ratio of different types of edges. Therefore, we transform the objective of minimizing the friends-to-rejections ratio and extend KL to the rejection-augmented social graphs.

The core of our transformation is a conversion of our problem targeting a ratio objective to a set of partitioning problems each with a linear objective function that is compatible with KL. We then extend the KL algorithm to solve each derived problem. Specifically, instead of directly minimizing the friends-to-rejections ratio $\frac{|F(\bar{U},U)|}{|\vec{R}\langle\bar{U},U\rangle|}$, we examine a family of cuts that minimize $|F(\bar{U},U)| - k \times |\vec{R}\langle\bar{U},U\rangle|$, where k is a positive parameter. The cut among the family that yields the lowest friends-to-rejections ratio is the solution (Theorem 1). We then extend the KL approach to solve each partition problem that minimizes $|F(\bar{U},U)| - k \times |\vec{R}\langle\bar{U},U\rangle|$.

Theorem 1: In a rejection-augmented social graph, if the cut $C^* = \langle U^*, \bar{U}^*\rangle$ is the minimum aggregate acceptance rate (MAAR) cut, and $\frac{|F(\bar{U}^*,U^*)|}{|\vec{R}\langle\bar{U}^*,U^*\rangle|} = k^*$ ($k^* > 0$), C^* is the optimal solution to the bipartition problem that minimizes $|F(\bar{U},U)| - k^* \times |\vec{R}\langle\bar{U},U\rangle|$.

Proof: Since $C^* = (U^*, \bar{U}^*)$ minimizes the aggregate acceptance rate, for any cut C' other than C^* we have $\frac{|F(\bar{U}',U')|}{|\vec{R}\langle\bar{U}',U'\rangle|} > \frac{|F(\bar{U}^*,U^*)|}{|\vec{R}\langle\bar{U}^*,U^*\rangle|}$. Hence, $\frac{|F(\bar{U}',U')|}{|\vec{R}\langle\bar{U}',U'\rangle|} > k^*$. This indicates $|F(\bar{U}',U')| - k^* \times |\vec{R}\langle\bar{U}',U'\rangle| > 0$ for any cut C' other than C^*. On the other hand, $|F(\bar{U}^*,U^*)| - k^* \times |\vec{R}\langle\bar{U}^*,U^*\rangle| = 0$ due to $\frac{|F(\bar{U}^*,U^*)|}{|\vec{R}\langle\bar{U}^*,U^*\rangle|} = k^*$. Therefore, C^* is the optimal solution to the partition problem minimizing $|F(\bar{U},U)| - k^* \times |\vec{R}\langle\bar{U},U\rangle|$. ■

Theorem 1 indicates that one can always find the MAAR cut (with the minimum friends-to-rejections ratio) by solving the above described family of problems for varying values of k. To approximate the aggregate friends-to-rejections ratio k^* of a MAAR cut, we iterate k through a geometric sequence, and pick the one that yields the lowest aggregate ratio.

KL Extension. We now describe how the KL approach can be extended to solve the partition problem minimizing $|F(\bar{U},U)| - k \times |\vec{R}\langle\bar{U},U\rangle|$, given a value for k. Our approach is to unify the friendship edges and the rejection edges by assigning them different weights according to the objective function, i.e., weight 1 and weight $-k$ for friendship and rejection, respectively. This conversion translates the objective into minimizing the sum of weight of the cross-region edges. Thus, it enables an extension of KL with edge weights to solve the problem. Algorithm 1 shows the pseudocode of our KL extension. Unlike in the graph partitioning problem that the original KL copes with, we do not assume prior knowledge on the part sizes of a partition. Thus, we replace the node-pair interchanging in KL with single-node switching to allow the change of part sizes. The bucket list dynamically indexes each node based on its potential gain of switching to the other part of the partition. To ensure a desirable approximation of the optimal cut with a ratio k^*, we iterate k through a geometric sequence with a certain scale factor.

Algorithm 1 ExtendedKL ($G(V, F, \vec{R})$, k, initPartition)

```
1: p = initPartition
2: repeat
3:    // Initiate the switching gain for each node
4:    nodeGainList = BucketList.init(p)
5:    nodeSwitchingSeq = $\emptyset$
6:    p_tmp = p  // Used to get the node-switching series
7:    while nodeGainList $\neq \emptyset$ do
8:       u = nodeGainList.getMaxGainNode()
9:       nodeSwitchingSeq.add(u)
10:      p_tmp.switch(u)
11:      nodeGainList.delete(u)
12:      // Update the gain of u's each neighbor according
13:      // to the objective $|F(\bar{U},U)| - k \times |\vec{R}\langle\bar{U},U\rangle|$
14:      nodeGainList.update(neighbor(u), p_tmp)
15:   end while
16:   // Get the prefix of nodeSwitchingSeq with the largest
17:   // positive decrement  in $|F(\bar{U},U)| - k \times |\vec{R}\langle\bar{U},U\rangle|$
18:   prefix = nodeSwitchingSeq.getMaxGainPrefix()
19:   p.switch(prefix)
20: until prefix == $\emptyset$
21: return p
```

E. Iteratively detecting fake-account groups

Fake accounts can form multiple independent groups. These groups may have few OSN links and rejections between them (Figure 6). In such cases, a single run of the extended KL algorithm catches only a few groups if the aggregate acceptance rates of requests from the rest of the fake groups are not equally low. To make it worse, a group of fake accounts can attempt to mimick real users by rejecting accounts from other groups controlled by the same attacker, i.e., by employing self-rejection. In an augmented social graph, fake accounts can craft an arbitrarily low friend-rejection ratio cut within themselves. In this way, attackers can whitewash a portion of their accounts by fabricating a cut within the collective of their fake accounts and making this cut's friends-to-rejections ratio even lower than the global friends-to-rejections ratio between the legitimate and the fake accounts, as shown in Figure 8. As a result, a scheme simply seeking the MAAR cut can miss the group of the rejecting fake accounts.

To address this challenge, Rejecto iteratively runs the extended KL to identify and cut off spammer groups from the graph until it has detected as many friend spammers as the OSN has estimated that exist (by inspecting sampled users [8], [15]). Attackers cannot change the friends-to-rejections ratio of the global spammer/legitimate cut, but they can craft a cut with a ratio lower than that within their fake accounts. In such cases, Rejecto first finds the lower ratio cuts within the fake accounts, and detects the part of the fake accounts that receive a large number of rejections due to the crafted low ratio. It then prunes these accounts with their links and rejections from the graph, and continues to find the next lowest friends-to-rejections ratio cut. This process repeats until we find the

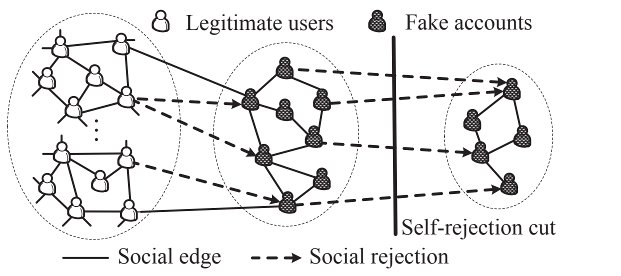


Fig. 8: Attackers whitewash a part of fake accounts by making them reject others as legitimate users do. In this illustration, the attacker attempts to whitewash the group of fake accounts in the middle.

global spammer/legitimate cut. By iteratively removing identified Sybils and their links and rejections, Rejecto gradually uncovers those whitewashed accounts.

Other termination conditions. In practice, besides the number of the estimated fake accounts, other conditions are also available to decide on the proper termination of the iterative cut detection procedure. Because we detect the MAAR cut of a residual graph in each round, the groups of suspicious accounts we uncover are in a non-decreasing order, in terms of the aggregate acceptance rate of their requests. Thus, multiple rounds of MAAR cut detection yield an ordered list of suspicious-account groups, among which those with a low aggregate request acceptance rate are uncovered first. As a result, an OSN provider can set an appropriate aggregate acceptance rate threshold (e.g., an estimate of the acceptance rate of normal users) and use it to terminate the iterative detection procedure.

F. *Reducing false positives*

The extended KL approach approximates the MAAR cut by interchanging nodes. Due to the large search space in a social graph, it might be stuck in a local minimum ratio cut, if that cut ratio is small. Although such small ratio cuts are rare among legitimate users, false positives can be introduced if one of them is mistakenly detected as a valid MAAR cut.

To reduce the false positives, we incorporate OSN providers' prior knowledge into the KL scheme. An OSN provider can determine whether a few selected users are fake accounts or legitimate through manual inspection. These users are randomly selected and we call them *seeds*. We use this knowledge to guide the KL partitioning to avoid cut mistakes.

Our idea is to pre-place each seed into its corresponding spammer or legitimate region and never switch it during the KL cut search. As a result, in a partition that Rejecto finds, the legitimate seeds and the fake account seeds always stay within the legitimate and the spammer regions, respectively. By distributing seeds over the entire graph, Rejecto can effectively rule out those problematic legitimate-user cuts from its search space. In particular, the undesirable partitions derived from such small cuts within the legitimate region misclassify portions of legitimate users as fake accounts, which, with high probability, conflicts with the pre-placement of the seeds. Therefore, as seeds never switch regions, Rejecto avoids the problematic cuts. To ensure sufficient seed coverage, one could employ the community-based seed selection as in SybilRank [15].

V. Implementation

We have implemented a Rejecto prototype [4]. It is layered on top of Spark [39], a generic in-memory large-data processing platform with automated fault tolerance. To obtain a scalable and efficient implementation, we distribute the large social graph structure to the workers, while keeping only a tractable set of algorithm variables and states on the master. This data layout ensures that Rejecto can handle large OSN data sets by scaling the capacity of the workers, and that the master can efficiently schedule the Rejecto algorithm according to the algorithm states kept on it. Using Spark's key feature, we cache intermediate data sets and results in memory, reducing the cost of their future reuse by Rejecto.

Architecture. In Rejecto, the update of node status, i.e., the partitioning part that a node belongs to, and the potential interchange gain if a node switch from one part of the partition to the other, is the most frequent operation. If we distribute the status of nodes to workers, the update of node status incurs delay by the network I/O between the master and the workers. Consequently, we keep on the master the node status with the potential switching gain and the bucket list that indexes the nodes. This reduces the network I/O during node status updates, at the cost of constant memory consumption per node on the master. If we have one billion nodes in an OSN and we uses 20 bytes to store a node status, this costs 20 GB memory in total, which is reasonable on commodity clusters.

Since the social graph, including social links and rejections, can be huge, we distribute its data to the workers as Resilient Distributed Datasets (RDDs) handled by Spark. The associated graph structure of a node can then be pulled to the master via a filter() transformation and a collect() action. We use a set of operations on RDDs to initialize the algorithm, including computing the numbers of initial cross-region friendships and rejections, and the initial potential gains on each node.

Reducing the network I/O with prefetching. Rejecto switches the node with the largest gain at each step and takes its social graph structure to adjust the status of its associated nodes. Since the social graph is held on the workers, the master needs to fetch the social graph structure via network I/O. A straightforward implementation would fetch the per-node social graph structure on demand, which leads to prohibitive overhead on the network communication between the master and the workers. To reduce the network I/O, we prefetch a set of nodes each time instead of just one node. Thus the movement of the prefetched nodes does not trigger any network I/O. The prefetched nodes are those with the highest potential move gains in the bucket list, and hence are likely to be accessed in near future. In our implementation, we dedicate a memory space to buffer the prefetched nodes with their social links and social rejections. Rejecto uses a LRU replacement strategy to evict nodes from the buffer.

VI. Evaluation

In this section, we evaluate Rejecto's effectiveness and compare it to VoteTrust, which ranks users on the friend request graph to detect fake accounts [35]. We choose VoteTrust for comparison because it also uses rejections of friend requests. We assess the two systems under: a) the flooding of spam requests; b) the collusion and self-rejection evasion strategies; and c) the rejection of legitimate requests by spammers. Moreover, we demonstrate the plausibility of combining Rejecto and social-graph-based approaches to form a defense in depth against fake accounts. Lastly, we evaluate the computational efficiency of our parallel implementation.

VoteTrust. It generates a user ranking for fake account detection via two steps. First, it uses a PageRank-like algorithm to assign a trust value for each user, called votes, using the directed friend request graph. Second, it generates a rating for each user that depends on the responses that his requests received, which is called vote aggregation. The rating of a user is a weighted average of 1s (accepted requests) and 0s (rejected requests). The weight of a request is the number of votes of the user that the request goes to times the current rating of that user. This rating computation takes place iteratively.

VoteTrust has two major weaknesses. First, the vote aggregation relies heavily on the request acceptance rate of each individual user, hence it is not resilient to collusion attacks (§VI-C). It is even unclear whether it is necessary to aggregate votes via an iterative computation. Second, it assumes that because the fake accounts have few incoming friend requests, the votes of a fake account assigned by a PageRank-like algorithm are low. However, attackers can manipulate PageRank values if they control accounts to send requests to each other [18]. Given these issues and vulnerabilities in each single step of VoteTrust, it is difficult to retain a meaningful defense by cascading the vote assignment and the vote aggregation.

TABLE I: Social graphs used in the simulation.

Social Network	Nodes	Edges	Clustering Coefficient	Diameter
Facebook	$10,000$	$40,013$	0.2332	17
ca-HepTh	$9,877$	$25,985$	0.2734	18
ca-AstroPh	$18,772$	$198,080$	0.3158	14
email-Enron	$33,696$	$180,811$	0.0848	13
soc-Epinions	$75,877$	$405,739$	0.0655	15
soc-Slashdot	$82,168$	$504,230$	0.0240	13
Synthetic	$10,000$	$39,399$	0.0018	7

A. Simulation setup

Data sets. We simulate friend spam on a Facebook sample graph, five public social graph data sets [5], and a synthetic graph, as shown in Table I. The Facebook graph is a sample graph we obtained on Facebook via the "forest fire" sampling method [28]. The synthetic graph is generated based on the scale-free model [14]. Our analysis focuses on the representative results on the Facebook graph. The results on other graphs are similar, as shown in Figure 17 (§A) and Figure 18 (§B).

On each social graph, we add a large spamming region with 10K fake accounts for stress-test. Upon the arrival of each fake account, it connects to 6 other fake accounts. Scenarios with dense connections among fake accounts are evaluated in §VI-C. To stress-test Rejecto, we simulate legitimate users that may be as careless as to sent out friend requests to the spamming region. That is, we randomly select a small set of legitimate users (i.e., 15%) and let each of them ever send out only one friend request that gets accepted by a random user.

Metric. To detect suspicious accounts, Rejecto iteratively cuts off identified accounts until their number reaches 10K (as many as the injected fake accounts). With VoteTrust, we designate the 10K users with the lowest rating as suspicious. We used the features and parameter settings for VoteTrust as described in [35]. The above assumes that the OSN provider has an estimation of the total number of fake accounts in the system, as this is usually done in practice via inspection on sampled accounts [8], [15]. In an OSN deployment, Rejecto can use fine-tuned termination conditions, as described in §IV-E. We compare Rejecto against VoteTrust based on the *precision*: the ratio of the number of the detected fake accounts to the number of declared suspicious users. Since we let each scheme declare the same number of suspicious accounts as that of the fake accounts we have injected, the precision is identical to the *recall* [31]. A high value of precision/recall indicates high detection accuracy.

Simulating rejections. Based on a previous measurement study in RenRen [36], we set the rejection rate to 70% for fake accounts, and to 20% for legitimate users. We set scenarios to study the sensitivity to those rejection rates in §VI-B. We let each fake account send out 20 requests to legitimate users. The fraction of these requests that are rejected is the rejection rate. This is a moderate baseline attack setting. As will be shown (§VI-B), sending out more requests exposes more fake accounts to the detection systems. We evaluate Rejecto under flooding attacks in §VI-B. To simulate rejections among legitimate users, we compute the number of a user's rejections by taking into account the rejection rate and the number of friends he has on the social graph. This number is a simple function of the rejection rate and the number of his friends. We then assign the origins of these rejections to randomly selected non-friend legitimate users.

B. Sensitivity analysis

Impact of the spam request volume. We simulate flooding attacks, where attackers flood friend requests to legitimate users. To this end, we increase the number of requests that each fake account sends out, ranging from 5 to 50, with a fixed rejection rate 70%. Figure 9 shows that Rejecto retains a high detection accuracy regardless of the number of requests per fake account. In contrast, VoteTrust's accuracy is low when the number of requests is small, and improves as the number of

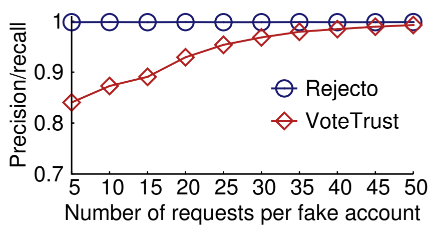


Fig. 9: **Precision/recall as a function of the number of requests per fake account, when we let all fake accounts send friend spam.**

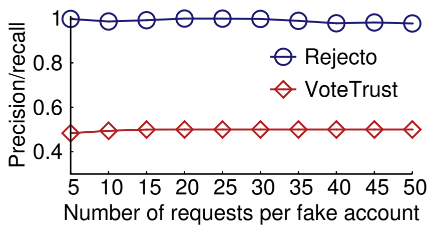


Fig. 10: **Precision/recall as a function of the number of requests per fake account, when half of the fake accounts send friend spam.**

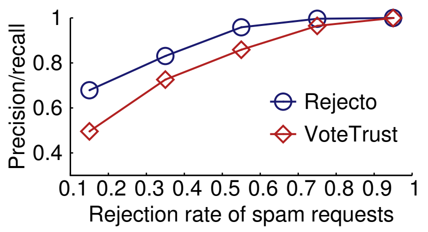


Fig. 11: **Precision/recall as a function of the rejection rate of spam requests.**

requests increases. This is because VoteTrust does not directly target the aggregate acceptance rate of the requests from fake accounts. Instead, it is sensitive to the volume of the requests due to its use of the PageRank-like vote assignment, i.e. the fake accounts get less votes if they send out more requests.

Fake accounts may probe legitimate users in a stealthy way in which only a part of them sends out requests. Attackers may attempt to protect some of their accounts from getting rejections. To this end, they use only a portion of their accounts to sent friend requests to legitimate users. At the same time, to avoid being isolated, the rest of their accounts connect to the spamming accounts. To assess our system under this strategy, we simulate attacks in which only half of the fake accounts flood friend requests. As shown in Figure 10, Rejecto withstands this attack because of the unchanged high rejection rate of the spam requests. Rejecto does not place the non-request-sending fake accounts into the legitimate region, because doing so would yield a higher acceptance ratio as these accounts are connected to the fake accounts that send out spam requests. VoteTrust is as low as 50%, indicating that it misses almost all the fake accounts that do not send friend requests. This is because VoteTrust's vote aggregation relies on the request acceptance rate of individual users. It missed the fake accounts behind the spamming accounts.

Sensitivity to the rejection rate of spam requests. We examine the impact of the rejection rate of spam requests by varying its value from 0.5 to 0.95. Figure 11 shows that the increasing rejection rate of spam requests results in improved accuracy for both Rejecto and VoteTrust. Rejecto and VoteTrust do not achieve high detection accuracy when the rejection rate is small. Besides, Rejecto can detect almost all of the fake accounts if the rejection rate of their requests is close to 60%.

Sensitivity to the rejection rate of legitimate requests. We evaluate the sensitivity to the rejection rate among legitimate users. We increase the rejection rate of legitimate requests from 0.05 to 0.95, while fixing that of spam requests to 0.7. As shown in figure 12, the accuracy of Rejecto and VoteTrust degrades with the increase of the rejection rate of legitimate requests. This is because the gap of the request rejection rate between fake and legitimate users shrinks, which makes them less distinguishable.

C. *Resilience to collusion and self-rejection*

We evaluate the resilience of Rejecto to the collusion and self-rejection detection evasion strategies.

Collusion between fake accounts. This attack strategy can improve the acceptance rate of requests from individual fake accounts, resulting in the ineffectiveness of simple spam filters [16], [36]. We evaluate Rejecto's resilience to the dense connections formed among fake accounts. Specifically, we vary the number of per-account accepted friend requests between fake accounts from 4 to 40. Figure 13 shows that Rejecto's accuracy remains high as the average rejection rate of a fake account drops from 70% to 23%. This is because the edges between colluders do not change the aggregate acceptance rate of their requests to legitimate users. In contrast, VoteTrust's accuracy degrades as the edges among spammers become denser, because it relies heavily on the number of requests from and the rejections to individual users.

Self-rejection within fake accounts. We evaluate Rejecto under the self-rejection strategy (§IV-E). In this simulation, attackers attempt to whitewash $5K$ fake accounts and disguise them as legitimate users by rejecting other fake accounts. We let each of the other $5K$ fake accounts send 20 requests to the fake accounts to be whitewashed. We increase the rejection rate of these requests from 0.05 to 0.95. We can see in Figure 14 that the accuracy of Rejecto remains high, except for the slight degradation when the rejection rate is close to 0.7, which is the rejection rate of requests from fake to legitimate users. This is because the ratio of the spammer/legitimate cut is too close to that of the cut within the fake account region, such that our algorithm is not able to precisely pinpoint it. When the self-rejection rate is larger than 0.7, Rejecto repeatedly solves MAAR, which detects the $5K$ request-sending fake accounts first, and then the whitewashed accounts. Unsurprisingly, we can also see that the self-rejection strategy is counterproductive against VoteTrust. At the beginning VoteTrust uncovers only the rejecting fake accounts, because they got rejections from legitimate users. The accuracy of VoteTrust improves as attackers add more rejections among fake account. This is because these additional rejections only hurt the acceptance rate of each individual fake account.

Rejection of legitimate friend requests by spammers. While real users do not usually get rejections from

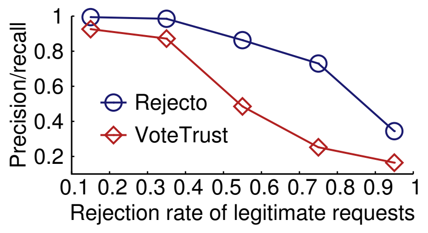


Fig. 12: **Precision/recall as a function of the rejection rate of the friend requests among legitimate users.**

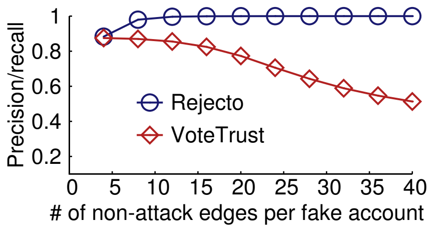


Fig. 13: **Resilience to the collusion strategy of forming dense social connections among fake accounts.**

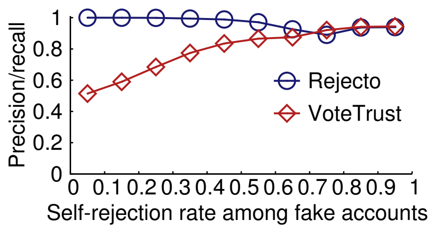


Fig. 14: **Resilience to the self-rejection strategy, which whitewashes a portion of fake accounts.**

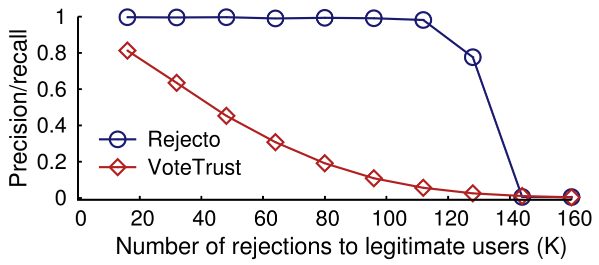


Fig. 15: **Precision/recall as a function of the number of rejections from fake to legitimate users.**

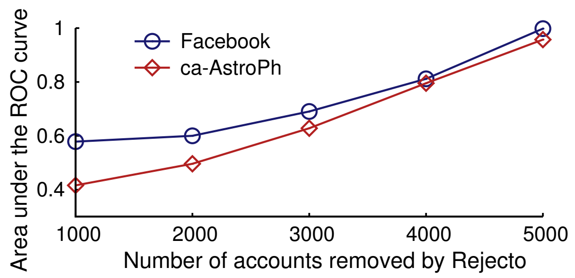


Fig. 16: **Ranking quality of SybilRank as a function of the number of suspicious users removed by Rejecto.**

a spamming account, we stress-test Rejecto by adding different numbers of rejections on legitimate users from the the spamming region. By this, we aim to account for careless users and spamming accounts that attempt to act strategically. The number of friend requests from legitimate users to fake accounts varies from $16K$ to $160K$, and all are rejected. At the same time, the number of rejections from legitimate to fake accounts is fixed at $140K$ (20 requests for each of the $10K$ fake accounts with a rejection rate of 70%). As shown in Figure 15, the detection accuracy of Rejecto is high when we add less than $120K$ rejections of legitimate requests. This indicates that Rejecto can tolerate a large number of legitimate users' rejections sent by Sybils. The detection accuracy drops abruptly when we add a number of rejections close to $140K$. This is because this large number of rejections has made legitimate users like spammers. On the other hand, the accuracy of VoteTrust decreases almost linearly, which indicates it is very sensitive to the rejections on legitimate users.

D. Defense in depth with social-graph-based Sybil detection

Rejecto can be used in combination with social-graph-based schemes to systematically detect Sybils (§II-C). We choose SybilRank [15] as a representative social-graph-based detection scheme, and run it on social graphs after removing a number of accounts that Rejecto declares as friend spammers. We use the value of area under the ROC curve [15] to measure the quality of the ranking of SybilRank. We add a 10K-Sybil set, among which 5K Sybils send out 20 spam requests, each at a rejection rate of 70%. Figure 16 shows the improvement of SybilRank's accuracy on our Facebook sample graph and the ca-AstroPh social graph [5], as the number of users that are removed by Rejecto increases. This improvement is because our system detects spamming accounts whose removal can reduce a significant fraction of attack edges in the social graph. If we let Rejecto remove 5K suspicious users, the area under the ROC curve of SybilRank's ranked list is close to 1, indicating that SybilRank detects most of the rest of the Sybils by ranking them to the bottom of its ranked list.

E. Computational cost on large graphs

TABLE II: **Rejecto's execution time with respect to the input graph size, and cluster capacity.**

#users	#edges	Cluster size	Aggregate RAM	Time
0.5M	$\sim$ 8M	5	300 GB	288 sec
1M	$\sim$ 16M	5	300 GB	669 sec
2M	$\sim$ 32M	5	300 GB	1767 sec
5M	$\sim$ 80M	5	300 GB	8049 sec
10M	$\sim$ 160M	5	300 GB	7.7 hours

We now present an assessment of Rejecto's computational efficiency aiming to show that our design is computationally practical, i.e., that it can process large OSN-scale graphs using a reasonably sized cluster within a sufficiently small amount of time.

We use an EC2 cluster running Spark 0.9.2 with 60GB RAM c3.8xlarge machines. In all cluster configurations, we have one master node and the rest of the nodes are workers. As we can see in Table II the system scales almost linearly with the size of the graph, provided that the volume of the aggregate memory in the cluster suffices. Because KL is a nearly linear-time algorithm [21], we anticipate that on a cluster with sufficient capacity (e.g., 100 worker nodes each with 40-60GB RAM and a master node with $\sim$200GB RAM), Rejecto can process social graphs with hundreds of millions of users.

VII. Discussion

Responses to the detected accounts. To prevent detected accounts from sending out friend spam in the future, an OSN provider can take actions, such as sending CAPTCHA challenges, rate-limiting their online activities, or even suspending the accounts [15], [32]. The actions taken before account suspension allow certain degree of tolerance to the false positives (e.g., OSN creepers [32]) in the detection system.

Application to the detection of other malicious accounts. The underlying friend spam model enables Rejecto to detect accounts that send out excessive friend requests but get a few accepted by legitimate users. OSN providers can apply it to the detection of other malicious accounts [17], such as compromised ones. If compromised accounts are manipulated to pollute the social graph via friend spam, their requests follow Rejecto's friend spam model. Therefore, they are exposed to Rejecto's detection. In such a deployment scenario, the OSN provider can shard friend requests and rejections according to the time intervals in which they have occurred, and then run Rejecto on an augmented graph constructed from the sharded requests and rejections in each interval. This enables Rejecto to detect compromised accounts in post-compromise intervals.

VIII. related work

Our work is mostly related to VoteTrust [35], which we summarize and experimentally compare to in Section VI. Cao et al. [16] also proposed to leverage user negative feedback to improve social-graph-based Sybil defense schemes. However, that design does not seek the aggregate acceptance ratio and is susceptible to attack strategies.

Rejecto is also related to social-graph-based Sybil defenses [15], [19], [33], [37]. These proposals rely on social graph properties to distinguish Sybils from non-Sybil users, i.e., that the number of edges connecting Sybil with non-Sybil nodes is relatively small. But, fake accounts benefit from soliciting OSN links via spammy friend requests because a non-negligible portion of users does not scrutinize, but accept them. Rejecto complements the aforementioned defenses. It cleans the social graph of the fake accounts that have obtained social edges, but in the process also have received many social rejections.

There is a plethora of studies on trust propagation in signed social networks [20], [23], [26], [40], where a social network contains both positive and negative edges. Unlike Rejecto, they do not use the aggregate acceptance rate, thus they are susceptible to manipulation. Moreover, they consider negative votes and ratings that malicious users can arbitrarily cast. As a result, they are not resilient to user distortion.

Recent work in signed social networks studies the "structure balance" [29]. The *structural balance theory* examines the signs of the edges of each interconnected three nodes, called a *triad*. A triad is balanced if the signs of edges respect the principles that "the friend of my friend is my friend", "the friend of my enemy is my enemy", "the enemy of my friend is my enemy", and "the enemy of my enemy is my friend". A network is balanced if all 3-node triads are balanced. Nevertheless, it is unclear how the structure balance theory could be used to detect friend spammers.

IX. Conclusion

The consequences of exploitation in the hands of unscrupulous users that create fake accounts (Sybils) are suffered by Online Social Network users and operators alike. We contribute to the fight against fake accounts that act as friend spammers in Facebook-like symmetric OSNs, driven by the observation that even well-maintained fake accounts inevitably have their friend requests rejected by legitimate users. To this end, we propose Rejecto, a system that detects accounts that send out unwanted friend requests. Rejecto augments the social graph with social rejections, and seeks the minimum aggregate acceptance rate cut. With this formulation, our system is able to uncover friend spammers in a manipulation-resistant way. We evaluate Rejecto through extensive simulations that are driven with real-world OSN samples. We also evaluate our parallel implementation on an EC2 cluster. Our evaluation results show that Rejecto is effective in a broad range of scenarios, resilient to attack strategies, and computationally practical.

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Appendix

A. *Additional sensitivity analysis results*

Figure 17 shows the additional results on sensitivity analysis (§VI-B) on the other six graphs in Table I. We examined the scenarios where the request volume varies when all fake accounts send requests and only half do so, where the rejection rate of spam requests from Sybils varies, and where the rejection rate of the requests among legitimate users varies. We can see that the detection accuracy of each scheme in these scenarios shows similar trends as we described in §VI-B.

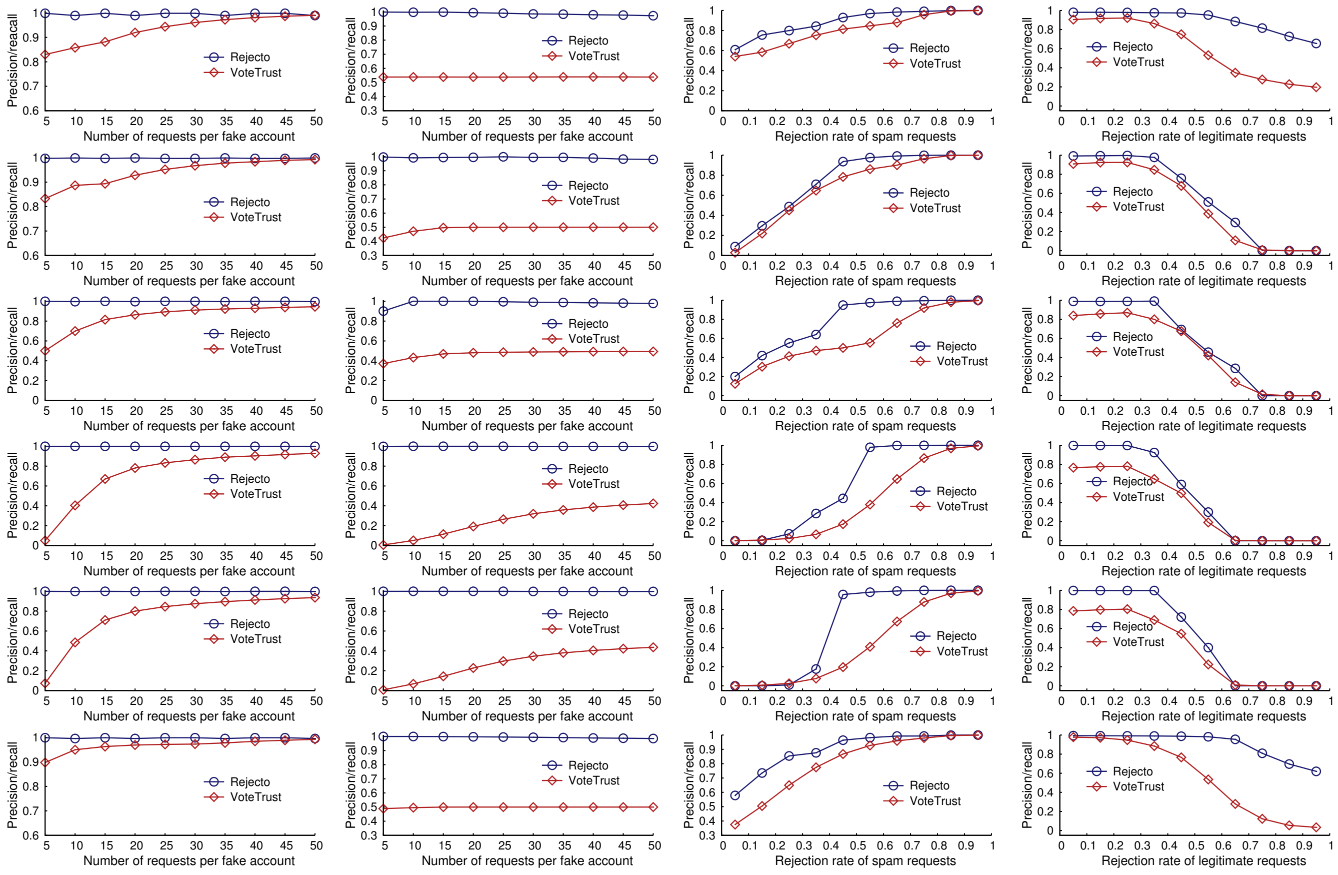

Fig. 17: Simulation results for sensitivity analysis on six social graphs under various attack settings. Starting from the top, the results in each row are obtained on the graphs ca-HepTh, ca-AstroPh, email-Enron, soc-Epinions, soc-Slashdot, and the synthetic graph, respectively. From left to right, the results in each column are obtained in each of the following scenarios: a) the request volume varies when all Sybils send spam requests; b) the request volume varies when half of the Sybils send spam requests; c) the rejection rate of spam requests from Sybils varies; d) the rejection rate of the requests among legitimate users varies. We compare the detection accuracy of Rejecto against VoteTrust.

B. *Additional results on strategy resilience*

Figure 18 shows the additional evaluation results on Rejecto's resilience to the collusion and self-rejection detection evasion strategies, and to the attack strategy that tricks legitimate users into sending requests to fake accounts and gets them rejected. We can see that the results on the other six graphs (Table I) show similar trends described in §VI-C, as we vary the capacity of the attackers in each scenario.

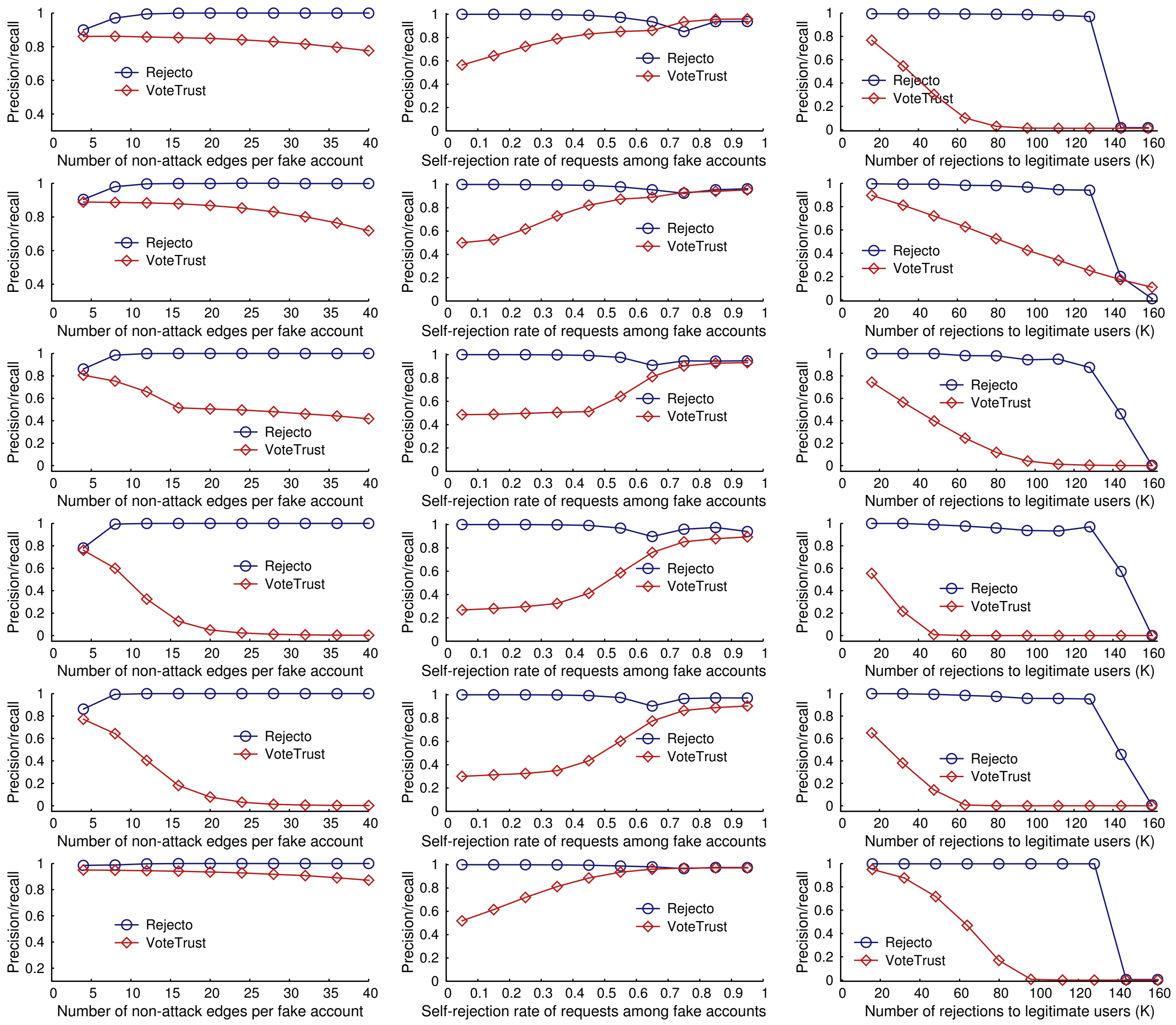

Fig. 18: Simulation results on six social graphs under attack strategies. Starting from the top, the results in each row are obtained on graphs ca-HepTh, ca-AstroPh, email-Enron, soc-Epinions, soc-Slashdot, and the synthetic graph, respectively. From left to right, the results in each column are obtained under: a) collusion, b) self-rejection, and c) legitimate users' requests being rejected by Sybils, respectively. In each attack scenario, we vary the capacity of the attackers. We compare the detection accuracy of Rejecto against VoteTrust.