Pisces: Anonymous Communication Using Social Networks

Prateek Mittal
University of California, Berkeley
pmittal@eecs.berkeley.edu

Matthew Wright
University of Texas at Arlington
mwright@cse.uta.edu

Nikita Borisov
University of Illinois at Urbana-Champaign
nikita@illinois.edu

***Abstract*—The architectures of deployed anonymity systems such as Tor suffer from two key problems that limit user's trust in these systems. First, paths for anonymous communication are built without considering trust relationships between users and relays in the system. Second, the network architecture relies on a set of centralized servers. In this paper, we propose *Pisces*, a decentralized protocol for anonymous communications that leverages users' social links to build circuits for onion routing. We argue that such an approach greatly improves the system's resilience to attackers.**

A fundamental challenge in this setting is the design of a secure process to discover peers for use in a user's circuit. All existing solutions for secure peer discovery leverage structured topologies and cannot be applied to unstructured social network topologies. In Pisces, we discover peers by using random walks in the social network graph with a bias away from highly connected nodes to prevent a few nodes from dominating the circuit creation process. To secure the random walks, we leverage the *reciprocal neighbor policy*: if malicious nodes try to exclude honest nodes during peer discovery so as to improve the chance of being selected, then honest nodes can use a tit-for-tat approach and reciprocally exclude the malicious nodes from their routing tables. We describe a fully decentralized protocol for enforcing this policy, and use it to build the Pisces anonymity system.

Using theoretical modeling and experiments on real-world social network topologies, we show that (a) the reciprocal neighbor policy mitigates active attacks that an adversary can perform, (b) our decentralized protocol to enforce this policy is secure and has low overhead, and (c) the overall anonymity provided by our system significantly outperforms existing approaches.

I. Introduction

Systems for anonymous communication on the Internet, or *anonymity systems*, provide a technical means to enhance user privacy by hiding the link between the user and her remote communicating parties (such as websites that the user visits). Popular anonymity systems include Anonymizer.com [8], AN.ON [3], [15], and Tor [13]. Tor is used by hundreds of thousands of users [55], including journalists, dissidents, whistle-blowers, law enforcement, and government embassies [18], [57].

Anonymity systems forward user traffic through a path (or *circuit*) of proxy servers. In some systems, including Tor, the proxies on the circuit are selected from among a large number of available proxies, each of which is supposed to be operated by a different person. An attacker, however, might run a substantial fraction of the proxies under different identities. He would then be able to deanonymize users whose circuits run through his attacker-controlled proxies. Thus, the security of the anonymity system hinges on at least some of the proxies in the circuit being honest [52]. Having some means to discern which proxies are likely to be honest would thereby greatly enhance the security of the system.

Recently, Johnson et al. proposed a method to incorporate *trust*—in which the user must judge which proxies are more likely to be honest—into a Tor-like system [24], [25]. However, their approach relies on central servers, and offers only limited scalability (see Section II). Both Nagaraja [41] and Danezis et al. [9] describe a compelling vision for leveraging social relationships in a decentralized (peer-to-peer) anonymity system by building circuits over edges in a social network graph. Unfortunately, their protocols are limited in applicability to a honest-but-curious attacker model. Against a more powerful Byzantine adversary, both approaches are vulnerable to *route capture attacks*, in which the entire circuit is comprised of malicious nodes. To our knowledge, no proposed system securely leverages social relationship information to improve the chances of attacker-free circuit construction in a decentralized anonymity system.

Our contributions: In this paper, we propose to use social networks to help construct circuits that are more robust to compromise than any prior approach among decentralized anonymity systems. We take advantage of the fact that, when protected from manipulation, random walks on social network topologies are likely to remain among the honest users [28], [63]. We thus propose to construct random walks on a social network topology to select circuits in such a way that they cannot be manipulated by a Byzantine adversary. We then build circuits from these protected random walks and show that they provide a very high chance for users to have an honest circuit, even for users who have a few social links to malicious peers.

The key challenge in this setting is to prevent the adversary from biasing the random walk by manipulating their routing tables. To this end, we propose the *reciprocal neighbor policy*: if malicious nodes try to exclude honest nodes during peer discovery, then honest nodes can use a tit-for-tat approach and reciprocally exclude the malicious nodes from their routing tables. The policy ensures that attempts to bias the random walk towards malicious nodes reduce the probability of malicious nodes being selected as intermediate nodes in the random walk, nullifying the effect of the attack. Further, to prevent an attacker from benefiting by creating a large clique of malicious peers in the social network, we bias random walks away from peers with many friends.

An important contribution of our work is a technique for enforcing the reciprocal neighbor policy in a fully decentralized fashion. We efficiently distribute each node's current list of contacts (using Whanau [28]) so that those contacts can verify periodically that they are in the list. A contact that should be in the list, but is not, can remove the node permanently from its contacts in future time periods. Further, the list is signed by the node, so any conflicting lists for the same time period constitute proof that the node is cheating. Using this policy, we design Pisces, a decentralized anonymity system that uses random walks on social networks to take advantage of users' trust relationships without being exposed to circuit manipulation.

We demonstrate through theoretical analysis, simulation, and experiments, that our application of the reciprocal neighbor policy provides good deterrence against active attacks. We also show that our distributed design provides robust enforcement of this policy, with manageable overhead for distributing and checking contact lists. Finally, using real world social network topologies, we show that Pisces provides significantly higher anonymity than existing approaches. Compared with decentralized approaches that do not leverage social networks (like ShadowWalker [37]), Pisces provides up to six bits higher entropy in a single communication round. Compared with the naive strategy of using conventional random walks over social networks (as in the Drac system [9]), Pisces provides twice the entropy over 100 communication rounds.

II. Background and Related Work

The focus of this work is on low-latency anonymity systems that can be used for interactive traffic such as Web browsing and instant messaging. Low-latency anonymity systems aim to defend against a partial adversary who can compromise or monitor only a fraction of links in the system. Most of these systems rely on *onion routing* [53] for anonymous communication. Onion routing enables anonymous communication by using a sequence of relays as intermediate nodes to forward traffic. Such a sequence of relays is referred to as a *circuit*. A key property of onion routing is that each relay on the circuit only sees the identity of the previous hop and the next hop, but no single relay can link both the initiator and the destination of the communication.

A. Centralized/semi-centralized approaches

Most deployed systems for anonymous communication have a centralized or semi-centralized architecture, including Anonymizer [8], AN.ON [15], Tor [13], Freedom [7], Onion Routing [53], and I2P [22]. Anonymizer.com [8] is effectively a centralized proxy server with a single point of control. If the proxy server becomes compromised or is subject to subpoena, the privacy provided by the system would be lost. AN.ON [15] distributes the trust among three independently-operated servers; again, the compromise of just a few nodes suffices to undermine the entire system. Both Anonymizer.com and AN.ON are prone to flooding-based denial of service attacks. Furthermore, with both systems, it may be possible to eavesdrop on the server(s) and use end-to-end timing attacks (such as [21], [61], [65]) to substantially undermine the privacy of all users.

Tor is a widely used anonymous communication system, serving roughly 500,000 users [56] and carrying terabytes of traffic each day [55]. Tor is substantially more distributed than either Anonymizer.com or AN.ON, with users building circuits from among about 3,000 proxy nodes (onion routers) as of May 2012 [27]. This helps to protect against direct attacks and eavesdropping on the entire system. Tor relies on trusted entities called *directory authorities* to maintain up-to-date information about all relays that are online in the form of a network consensus database. Freedom [7] and I2P [22] also use such centralized directory servers. Users download the full database, and then locally select random relays for anonymous communication. Clients download this database every three hours to handle relay churn.

Although Tor has a more distributed approach than any other deployed system, there are several shortcomings with its architecture. First, Tor does not leverage a user's trust relationships for building circuits. In Tor, an attacker could volunteer a set of proxy nodes under different identities and then use these nodes to compromise the anonymity of circuits going through them. Leveraging trust relationships has been shown to be useful for improving anonymity against such an attacker in Tor [24], [25]. Second, the trusted directory authorities are attractive targets for attack; in fact, some directory authorities were recently found to have been compromised [1]. Finally, the requirement for all users to maintain global information about all online relays becomes a scalability bottleneck. McLachlan et al. [32] showed that under reasonable growth projections, the Tor network could be spending more bandwidth to maintain this global system view than for the core task of relaying anonymous communications. The recent proposal for PIR-Tor [40] might address the networking scalability issues, but it does not mitigate the basic trust and denial of service issues in a centralized approach.

B. Incorporating social trust

The importance of leveraging social network trust relationships to improve the security and privacy properties of systems has been recognized by a large body of previous work [9]–[11], [24], [25], [28], [29], [39], [41], [58], [63], [64]. Recently, Johnson et al. proposed a method to incorporate trust into a Tor-like system [24], [25]. However, their approach relies on central servers, and offers only limited scalability. Nagaraja [41] and Danezis et al. [9] have both proposed anonymity systems over social networks. However, both approaches assume an honest-but-curious attack model and are vulnerable to route capture attacks. In particular, without the security of the reciprocal neighbor policy used in Pisces, a random walk on the social graph that goes to an attacker-controlled peer at any step can be controlled by the attacker for the remainder of the walk.

Designing anonymity systems that are aware of users' trust relationships is an important step towards defending against the *Sybil attack* [14], in which a single entity in the network (the attacker) can emulate the behavior of multiple identities and violate security properties of the system. Mechanisms like SybilGuard [64], SybilLimit [63], and SybilInfer [11] aim to leverage social network trust relationships to bound the number of Sybil identities any malicious entity can emulate. These mechanisms are based on the observation that it is costly for an adversary to form trust relationships (also known as *attack edges*) with honest nodes. When the adversary performs a Sybil attack, he can create an arbitrary number of edges between Sybil identities and malicious entities, but cannot create trust relationships between Sybil identities and honest users. Thus, a Sybil attack in social networks creates two regions in the social network graph, the honest region and the Sybil region, with relatively few edges between them; i.e., the graph features a *small cut*. This cut can be used to detect and mitigate the Sybil attack.

Recent work has challenged the assumption that it is costly for an attacker to create attack edges with honest nodes in friendship graphs [4], [6], [23], [62], and proposed the use of interaction graphs as a more secure realization of real world social trust. In this work, we will evaluate Pisces with both friendship graphs as well as topologies based on interaction graphs. Other mechanisms to infer the strength of ties between users [17] may also be helpful in creating resilient social graphs, but these are not the focus of this paper.

C. Decentralized and peer-to-peer approaches

A number of distributed directory services for anonymous communication have been designed using a P2P approach; most have serious problems that prevent them from being deployed. We point out these issues briefly here. First we note that the well-known Crowds system, which was the first P2P anonymity system, uses a centralized directory service [45] and thus is not fully P2P. The Tarzan system proposes a gossip-based distributed directory service that does not scale well beyond 10,000 nodes [16].

MorphMix was the first scalable P2P anonymity system [46]. It uses random walks on unstructured topologies for circuit construction and employs a *witness* scheme that aims to detect routing table manipulation. The detection mechanism can be bypassed by an attacker who is careful in his choices of fake routing tables [54]. With or without the evasion technique, the attacker can manipulate routing tables to capture a substantial fraction of circuits. Despite over a decade of research, decentralized mechanisms to secure random walks in unstructured topologies have been an open problem. Pisces overcomes this problem by having peers sign their routing tables for a given time slot and ensuring that nodes observe enough copies to detect cheaters quickly, before many route captures can occur, and with certainty.

Recently, several protocols have been proposed using P2P systems built on distributed hash tables (DHTs), including AP3 [35], Salsa [42], NISAN [43], and Torsk [32]. These four protocols are vulnerable to information leak attacks [36], [60], as the lookup process and circuit construction techniques expose information about the requesting peer's circuits. These attacks can lead to users being partially or completely deanonymized. ShadowWalker, which is also based on a structured topology, employs random walks on the DHT topology for circuit construction [37]. The routing tables are checked and signed by *shadow nodes* such that both a node in the random walk and all of its shadows would need to be attackers for a route capture attack to succeed. The protocol was found to be partially broken, but then also fixed, by Schuchard et al. [48]. Despite it not being seriously vulnerable to attacks as found against other protocols, ShadowWalker remains vulnerable to a small but non-trivial fraction of route captures (roughly the same as Tor for reasonable parameters). As we show in Section IV, Pisces's use of social trust means that it can outperform ShadowWalker (and Tor) for route captures when the attacker has a bounded number of attack edges in the social network.

Other than these approaches, Mittal et al. [38] briefly considered the use of the reciprocal neighbor policy for anonymous communication. However, their protocol is only applicable to constant degree topologies, and utilizes central points of trust. Moreover, their evaluation was very preliminary. In this paper, we present a complete design for a decentralized anonymity system based on the reciprocal neighbor policy. Since our design is not limited to constant degree topologies, we explore the advantages that come from applying the technique to unstructured social network graphs. We also present the first fully decentralized protocols for achieving these policies and present analysis, simulation, and experimentation results demonstrating the security and performance properties of the Pisces approach.

III. Pisces Protocol

In this section, we first describe our design goals, threat model, and system model. We then outline the core problem of securing random walks and describe the role of the reciprocal neighbor policy in solving the problem in the context of social networks. Finally, we explain how Pisces securely implements this policy.

A. Design goals

We now present our key design goals for our system.

1. *Trustworthy anonymity:* we target an architecture that is able to leverage a user's social trust relationships to improve the security of anonymous communication. Current mechanisms for incorporating social trust are either centralized or are limited in applicability to an honest-but-curious attacker model.

2. *Decentralized design:* the design should not have any central entities. Central entities are attractive targets for attackers, in addition to being a single point of failure for the entire system. The design should also mitigate route capture and information leak attacks.

3. *Scalable anonymity:* the design should be able to scale to millions of users and relays with low communication overhead. Since anonymity is defined as the state of being unidentifiable in a group [44], architectures that can support millions of users provide the additional benefit of increasing the overall anonymity of users.

B. Threat model

In this work, we consider a colluding adversary who can launch Byzantine attacks against the anonymity system. The adversary can perform passive attacks such as logging information for end-to-end timing analysis [30], as well as active attacks such as deviating from the protocol and selectively denying service to some circuits [5]. We assume the existence of effective mechanisms to defend against the Sybil attack, such as those based on social networks [11], [63]. Existing Sybil defense mechanisms are not perfect and allow the insertion of a bounded number of Sybil identities in the system. They also require the number of attack edges to be bounded by $g = O(\frac{h}{\log h})$, where h is the number of honest nodes in the system. We use this as our primary threat model. For comparative analysis, we also evaluate our system under an ideal Sybil defense that does not allow the insertion of any Sybil identities.

C. System Model and Assumptions

Pisces is a fully decentralized protocol and does not assume any PKI infrastructure. Each node generates a local public-private key pair. An identity in the system equates to its public key. Existing Sybil defense mechanisms can be used to validate node identities. We assume that the identities in the system can be blacklisted; i.e., an adversary node cannot whitewash its identity by rejoining the system with a different public key. This is a reasonable assumption, since (a) mechanisms such as SybilInfer/SybilLimit only allow the insertion of a bounded number of Sybil identities, and (b) replacing deleted attack edges is expensive for the attacker, particularly in a social network graph based on interactions. We assume loose time synchronization amongst nodes. Existing services such as NTP [34] can provide time synchronization on the order of hundreds of milliseconds in wide area networks [20].

Finally, in this work, we will leverage mechanisms for building efficient communication structures over unstructured social networks, such as Whanau [28] and X-Vine [39]. These mechanisms embed a structure into social network topologies to provide a distributed hash table for efficient communication [47], [51]. In particular, we use Whanau, since it provides the best security guarantees amongst the current state of art. Whanau guarantees that, with high probability, it is possible to securely look up any object present in the DHT. It is important to point out that Whanau only provides *availability*, but not *integrity* [28]. This means that if a user performs redundant lookups for a single key, multiple conflicting results may be returned; Whanau guarantees that the correct result will be included in the returned set, but leaves the problem of identifying which result is correct to the application layer. Therefore, Whanau cannot be used in conjunction with current protocols that provide anonymous communication using structured topologies [37], since these protocols require integrity guarantees from the DHT layer itself. We emphasize that the only property we assume from Whanau is secure routing; in particular, we do not assume any privacy or anonymity properties in its lookup mechanisms [36], [60].

D. Problem Overview

Random walks are an integral part of many distributed anonymity systems, from Tor [13] to ShadowWalker [37]. In a random walk based circuit construction, an initiator I of the random walk first selects a random node A from its neighbors in some topology (in our case, the social network graph). The initiator sets up a single-hop circuit with node A and uses the circuit to download a list of node A's neighbors (containing the IP addresses and public keys of neighbors). Node I can then select a random node B from the downloaded list of node A's neighbors and extend the circuit through A onto node B. This process can be repeated to set up a circuit of length l.

Random walks are vulnerable to active route capture attacks in which an adversary biases the peer discovery process towards colluding malicious nodes. First, malicious nodes can exclude honest nodes from their neighbor list to bias the peer discovery process. Second, malicious nodes can modify the public keys of honest nodes in their neighbor list. When a initiator of the random walk extends a circuit from a malicious node to a neighboring honest node, the malicious node can simply emulate the honest neighbor. The malicious node can repeat this process for further circuit extensions as well. Finally, the malicious nodes can add more edges between each other in the social network topology to increase the percentage of malicious nodes in their neighbor lists. To secure the random walk process, we use a reciprocal neighbor policy that limits the benefit to the attacker of attempting to bias the random walks. We propose a protocol that securely realizes this policy through detection of violations.

E. *Reciprocal Neighbor Policy*

We now discuss the key primitive we leverage for securing random walks, the *reciprocal neighbor policy*. The main idea of this policy is to consider undirected versions of structured or unstructured topologies and then entangle the routing tables of neighboring nodes with each other. In other words, if a malicious node X does not correctly advertise an honest node Y in its neighbor list, then Y also excludes X from its neighbor list in a tit-for-tat manner. The reciprocal neighbor policy ensures that route capture attacks based on incorrect advertisement of honest nodes during random walks serves to partially isolate malicious nodes behind a small cut in the topology, reducing the probability that they will be selected in a random walk. In particular, this policy mitigates the first two types of route capture attacks described above, namely the exclusion of honest nodes and the modification of honest nodes' public keys. However, the adversary can still bias the peer discovery process by simply inserting a large number of malicious nodes to its routing tables. Thus, the reciprocal neighbor policy described so far would only be effective for topologies in which node degrees are bounded and homogeneous, such as structured peer-to-peer topologies like Chord [51] and Pastry [47]. However, node degrees in unstructured social network topologies are highly heterogeneous, presenting an avenue for attack.

Handling the node degree attack: Addition of edges amongst colluding malicious nodes in a topology increases the probability that a malicious node is selected in a random walk. To prevent this node degree attack, we propose to perform random walks using the Metropolis-Hastings modification [19], [33] — the transition matrix used for our random walks is as follows:

$$P_{ij} = \begin{cases} \min(\frac{1}{d_i}, \frac{1}{d_j}) & \text{if } i \to j \text{ is an edge in G} \\ 1 - \sum_{k \neq i} P_{ik} & \text{if } j = i \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

where d_i denotes the degree of vertex i in G. Since the transition probabilities to neighbors may not always sum to one, nodes add a self loop to the transition probabilities to address this. The Metropolis-Hastings modification ensures that attempts to add malicious nodes in the neighbor table decreases the probability of malicious nodes being selected in a random walk. We will show that the Metropolis-Hastings modification along with reciprocal neighbor policy is surprisingly effective at mitigating active attacks on random walks. A malicious node's attempts to bias the random walk process by launching route capture attacks reduce its own probability of getting selected as an intermediate node in future random walks, nullifying the effect of the attack.

F. *Securing Reciprocal Neighbor Policy*

We now present our protocol for securely implementing the reciprocal neighbor policy.

Intuition: Our key idea is to have neighbors periodically check each other's neighbor lists. Suppose that node X and node Y are neighbors. If node X's neighbor list doesn't include node Y, then the periodic check will reveal this and enable node Y to implement the tit-for-tat removal of node X from its routing table. Additionally, the neighbor lists can be signed by each node so that a dishonest node can be caught with two different, signed lists and blacklisted. To handle churn, we propose that all nodes keep their neighbor lists static for the duration of a regular interval (t) and update the list with joins and leaves only between intervals. Here we rely on our assumption of loose time synchronization. The use of static neighbor lists ensures that we can identify conflicting neighbor lists from a node for the same time interval, which would be a clear indication of malicious behavior. The duration of the time interval for which the lists remain static determines the trade-off between the communication overhead for securing the reciprocal neighborhood policy and the unreliability of circuit construction due to churn.

Setting up static neighbor list certificates: A short time prior to the beginning of a new time interval, each node sets up a new neighbor list that it will use in the next time interval:

1) *Liveness check*: In the first round, nodes exchange messages with their trusted neighbors to check for liveness and reciprocal trust. A reciprocal exchange of messages ensures that both neighbors are interested in advertising each other in the next time interval (and are not in each other's local blacklists). Nodes wait for a time duration to receive these messages from all neighbors, and after the timeout, construct a preliminary version of their next neighbor list, comprising node identities of all nodes that responded in the first communication round.
2) *Degree exchange*: Next, the nodes broadcast the length of their preliminary neighbor list to all the neighbors. This step is important since Metropolis-Hastings random walks require node degrees of neighboring nodes to determine their transition probabilities.
3) *Final list*: After receiving these broadcasts from all the neighbors, a node creates a final neighbor list and digitally signs it with its private key. The final list includes the IP address, public key, and node degree of each neighbor, as well as the time interval for the validity of the list. Note that a neighbor may go offline

between the first and second step, before the node has a chance to learn its node degree, in which case it can simply be omitted from the final list.

4) *Local integrity checks*: At the beginning of every new time interval, each node queries all its neighbors and downloads their signed neighbor lists. When a node A receives a neighbor list from B, it performs local integrity checks, verifying that B's neighbor entry for A contains the correct IP address, public key, and node degree. Additionally, it verifies that the length of the neighbor list is at most as long as was broadcast in Phase 2. (Note that intentionally broadcasting a higher node degree is disadvantageous to a B, as it will reduce the transition probability of it being chosen by a random walk). If any local integrity checks fails, A places B in its permanent local blacklist, severing its social trust relationship with B and refusing all further communication. If all the checks succeed, then these neighbor lists serve as a cryptographic commitment from these nodes–the presence of any conflicting neighbor lists for the same time interval issued by the same node is clear evidence of misbehavior.

   If B's neighbor list omits A entirely, or if B simply refuses to send its neighbor list to A, B is placed on a temporary blacklist, and A will refuse further communication with B for the duration of the current time period, preventing any circuits from being extended from A to B. (Effectively, A performs a selective denial-of-service against B; see Section IV-C for more discussion of this.) The blacklist only lasts for the duration of the current round, since the omission could have resulted from a temporary communication failure.

Duplicate detection: Next, we need to ensure that B uses the same neighbor list during random walks as it presented to its neighbors. Our approach is to use the Whanau DHT to check for the presence of several conflicting neighbor lists signed by the same node for the same time period. After performing the local checks, A will store a copy of B's signed neighbor list in the Whanau, using B's identity (namely, its public key) as the DHT key. Then, when another node C performs a random walk that passes through B, it will receive a signed neighbor list from B. It will then perform a lookup in the DHT for any stored neighbor lists under B's key. If it discovers a different list for the same period with a valid signature, then it can notify B's neighbors about the misbehavior, causing them to immediately blacklist B.

One challenge is that the Whanau lookups are not anonymous and may reveal to external observers the fact that C is performing a random walk through B. This information leak, linking C and B, can then be used to break C's anonymity [36], [60]. To address this problem, we introduce the concept of *testing* random walks that are not actually used for anonymous communication but are otherwise indistinguishable from regular random walks. Whanau lookups to check for misbehavior are performed for testing random walks only, since information leaks in that case will not reveal private information. The lookups are performed after the random walk to ensure that testing walks and the regular walks cannot be distinguished. If each node performs a small number of testing walks within a each time period, any misbehavior will be detected with high probability.

Blacklisting: When C detects a conflicting neighbor list issued by B, it immediately notifies all of B's neighbors (as listed in the neighbor list stored in the DHT), presenting the two lists as evidence of misbehavior. B's neighbors will thereafter terminate their social relationships with B, blacklisting it. Note, however, that the two conflicting lists form incontrovertible evidence that B was behaving maliciously, since honest nodes *never* issue two neighbor lists in a single time interval. This evidence can be broadcast globally to ensure that *all* nodes blacklist B, as any node can verify the signatures on the two lists, and thus B will not be able to form connections with any honest nodes in the system. Moreover, honest nodes will know not to select B in any random walk, effectively removing it from the social graph entirely.

Proactive vs. reactive security: Our system relies on detecting malicious behavior and blacklisting nodes. Thus, as described so far, Pisces provides reactive security. To further strengthen random walk security in the scenario when the adversary is performing route capture for the first time, we propose an extension to Pisces that aims to provide proactive security. We propose a *discover but wait* strategy, in which users build circuits for anonymous communication, but impose a delay between building a circuit and actually using it for anonymous communication. If misbehavior is detected by a testing random walk within the delay period, the circuit will be terminated as B's neighbors blacklist it; otherwise, if a circuit survives some timeout duration, then it can be used for anonymous communication.

Performance optimization: Using all hops of a random walk for anonymous communication has significant performance limitations. First, the latency experienced by the user scales linearly with the random walk length. Second, long circuit lengths reduce the overall throughput that a system can offer to a user. Inspired by prior work [37], we propose the following performance optimization. Instead of using all hops of a random walk for anonymous communication, the initiator can use the random walk as a peer discovery process, and leverage the kth hop and the last hop to build a two-hop circuit for anonymous communication. In our evaluation, we find that values of k that are close to half the random walk length provide a good trade-off between anonymity and performance.

IV. Evaluation

In this section, we evaluate Pisces with theoretical analysis as well as experiments using real-world social network topologies. In particular, we (a) show the security benefits provided by the reciprocal neighbor policy, (b) evaluate the security, performance, and overhead of our protocol that implements the policy, and (c) evaluate the overall anonymity provided by Pisces. We consider four datasets for our experiments, which were processed in a manner similar to the evaluation done in SybilLimit [63] and SybilInfer [11]: (i) *a Facebook friendship graph from the New Orleans regional network [59]*, containing 50,150 nodes and 772,843 edges; (ii) *a Facebook wall post interaction graph from the New Orleans regional network [59]*, containing 29,140 users and 161,969 edges; (iii) *a Facebook interaction graph from a moderate-sized regional network [62]*, containing about 380,564 nodes and about 3.24 million edges; (iv) *a Facebook friendship graph from a moderate-sized regional network [62]*, containing 1,033,805 nodes and about 13.7 million edges.

A. Reciprocal Neighbor Policy

To demonstrate the effectiveness of the reciprocal neighbor policy for implementing trust-based anonymity, let us assume for now that there is a mechanism to securely achieve the policy, i.e., that if a node X does not advertise a node Y in its neighborlist, then Y also excludes X. In this scenario, we are interested in characterizing the probability distribution of random walks.

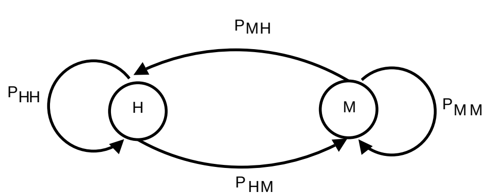


Fig. 3. Attack Model.

Theorem 1: Node degree attack: Given h honest nodes and m malicious nodes (including Sybil nodes) that have g edges (attack edges) amongst each other in an undirected and connected social network, the stationary probability of random walks starting at an honest node and terminating at a malicious node cannot be biased by adding edges amongst malicious nodes. Moreover, this stationary probability is independent of the topology created amongst malicious nodes (as long as the social graph is connected).

Proof: Let us denote π_i as the stationary probability of random walks (independent of the initial state of the random walk) for node i, and let P_{ij} denote the transition probability from node i to node j. Let n denote the total number of nodes in the social network ($n = h + m$). Since the transition probabilities between nodes in the Metropolis-Hastings random walks are symmetric ($P_{ij} = P_{ji} = \min\left(\frac{1}{degree(i)}, \frac{1}{degree(j)}\right)$), observe that $\forall z, \pi_z = \frac{1}{n}$ is solution to the equation $\pi_i \cdot P_{ij} = \pi_j \cdot P_{ji}$. Since social networks are non-bipartite as well as undirected graphs, the solution to the above equation ($\pi = \frac{1}{n}$) must be the unique stationary distribution for the random walk [2]. Thus the stationary probability of random walks terminating at any node in the system is uniform and independent of the number of edges amongst malicious nodes, or the topology amongst malicious nodes in the system (as long as the graph remains connected). ■

We validate Theorem 1 using simulation results on the Facebook wall post interaction graph. Figure 1(a) depicts the probability of a Pisces random walk terminating at a malicious node as a function of random walk length for $g = 30000$ (2900 malicious nodes) and $g = 60000$ (7300 malicious nodes). We can see that the random walk quickly reaches its stationary distribution, and at the stationary distribution, the probability of a random walk terminating at one of the malicious nodes is 0.1 and 0.25 respectively (which is the adversary's fair share). Figure 1(b) and (c) depict the probability of a random walk terminating at one of the malicious nodes under the node degree attack, for $g = 30000$ and $g = 60000$ respectively. We can see that adding edges amongst malicious nodes does not help the adversary (even for transient length random walks).

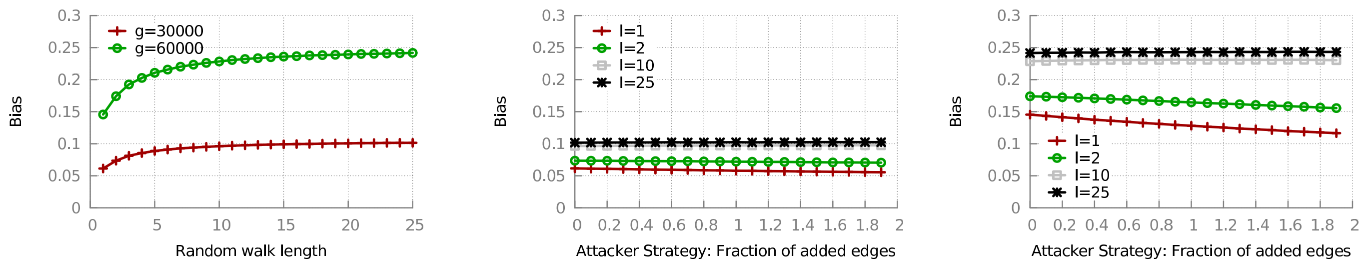
Theorem 2: Global blacklisting: suppose that $x \leq m$ malicious nodes sacrifice $y_1 \leq g$ attack edges, and that these malicious nodes originally had $y_2 \leq g$ attack edges. The stationary probability of random walk terminating at malicious nodes gets reduced proportional to x. The transient distribution of random walks terminating at malicious nodes is reduced as a function of y_2.

Proof: If x malicious nodes perform the route capture attack and are globally blacklisted, these nodes become disconnected from the social trust graph. It follows from our analysis of Theorem 1 that the stationary distribution of the random walk is uniform for all *connected* nodes in the graph. Thus, the stationary distribution of random walks terminating at malicious nodes gets reduced from $\frac{m}{m+h}$ to $\frac{m-x}{m-x+h}$.

To characterize the transient distribution of the random walk, we model the process as a Markov chain. Let us denote the honest set of nodes by H, and the set of malicious nodes by M. The probability of an l hop random walk ending in the malicious region ($P(l)$) is given by:

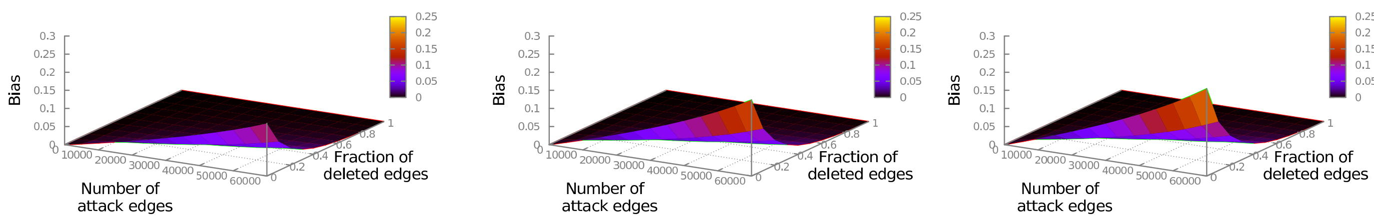
$$P(l) = P(l-1) \cdot P_{MM} + (1 - P(l-1)) \cdot P_{HM} \tag{2}$$

The terminating condition for the recursion is $P(0) = 1$, which reflects that the initiator is honest. We can estimate the probabilities P_{HM} and P_{MH} as the forward and backward conductance [26] between the honest and the malicious nodes, denoted by ϕ_F and ϕ_B respectively. Thus we have that:



(a) (b) (c)

Fig. 1. *Probability of the l'th hop being compromised (Sampling Bias), under an increasing node degree attack [Facebook wall post graph]* (a) Without attack (b) g=30000 attack edges, (c) g=60000 attack edges. For short random walks, this is a losing strategy for the adversary. For longer random walks, the adversary does not gain any advantage.



(a) (b) (c)

Fig. 2. *Probability of l'th hop being compromised (Sampling Bias) under route capture attack with global blacklisting [Facebook wall post graph]* (a) $l = 1$, (b) $l = 5$, (c) $l = 25$. As more edges to the honest nodes are removed, the attacker's loss is higher.

$$P(l) = P(l-1)\cdot(1-\phi_B) + (1-P(l-1))\cdot\phi_F$$
$$= P(l-1)\cdot(1-\phi_B-\phi_F)+\phi_F \quad (3)$$

$$P(l) = \phi_F \cdot [1 + (1-\phi_B-\phi_F) + (1-\phi_B-\phi_F)^2$$
$$\ldots + (1-\phi_B-\phi_F)^{l-1}] \quad (4)$$

We note that if an adversary connects a chain of Sybils (say of degree 2) to an attack edge, a random walk starting from an honest node and traversing the attack edge to enter the malicious region has a non-trivial probability of coming back to the honest region - via the attack edge (Pisces allows backward transition along edges). Our analysis models the probability of returning to the honest region using the notion of backward conductance.

With g edges between honest and malicious nodes, we can estimate the forward conductance ϕ_F as follows:

$$\phi_F = \frac{\Sigma_{x\in H}\Sigma_{y\in M}\pi_x\cdot P_{xy}}{\pi_H}$$
$$= \frac{\Sigma_{x\in H}\Sigma_{y\in M}\cdot P_{xy}}{|H|} = O\left(\frac{g}{h}\right) \quad (5)$$

Similarly, with g edges between honest and malicious nodes, the backward conductance ϕ_B is estimated as:

$$\phi_B = \frac{\phi_F\cdot|H|}{|M|} = \frac{O(\frac{g}{h})\cdot h}{m} = O\left(\frac{g}{m}\right) \quad (6)$$

Thus, we have that $\phi_F = O(\frac{g}{h})$, and $\phi_B = O(\frac{g}{m})$. If malicious nodes exclude y edges to honest nodes from their fingertables, application of the RNP ensures that the honest nodes also exclude the y edges from their fingertables (local blacklisting). Thus, route capture attacks result in deleting of attack edges which reduces both forward and backward transition probabilities. Observe that the probability of the first hop being in the malicious region is equal to ϕ_F, which gets reduced under attack. We will now show this for a general value of l. Following Equation 4 and using $\Sigma_{i=0}^{i=m}x^i = \frac{1-x^{m+1}}{1-x}$ for $0 < x < 1$, we have that:

$$P(l) = \frac{\phi_F\cdot(1-(1-\phi_B-\phi_F)^l)}{1-(1-\phi_B-\phi_F)}$$
$$= \frac{\phi_F}{\phi_F+\phi_B}\cdot(1-(1-\phi_B+\phi_F)^l) \quad (7)$$

Using $\phi_B = \frac{h}{m}\cdot\phi_F$, we have that:

$$P(l) = \frac{m}{n}\cdot(1-(1-\phi_B+\phi_F)^l)$$
$$P(l) = \frac{m}{n}\cdot\left(1-\left(1-\frac{n}{m}\cdot\phi_F\right)^l\right) \quad (8)$$

Differentiating $P(l)$ with respect to ϕ_F, we have that:

$$\frac{d}{d\phi_F}(P(l)) = \frac{m}{n}\cdot\left(l\cdot\left(1-\frac{n}{m}\cdot\phi_F\right)^{l-1}\right) \quad (9)$$

Note that $(1-\frac{n}{m}\phi_F) = (1-\phi_B-\phi_F) \geq 0$. This implies $\frac{d}{d\phi_F}P(l) \geq 0$. Thus, $P(l)$ is an increasing function of ϕ_F,

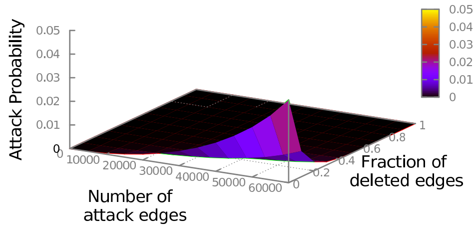


Fig. 4. Probability of end-to-end timing analysis under route capture attack with global blacklisting [Facebook wall graph]

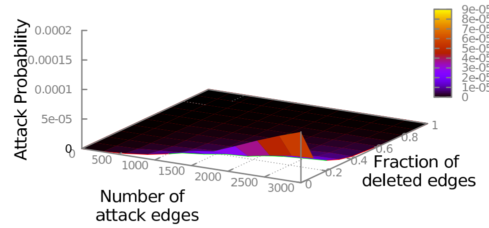


Fig. 5. Probability of end-to-end timing analysis under route capture attack with global blacklisting using 10 Sybils per attack edge [Facebook wall graph]

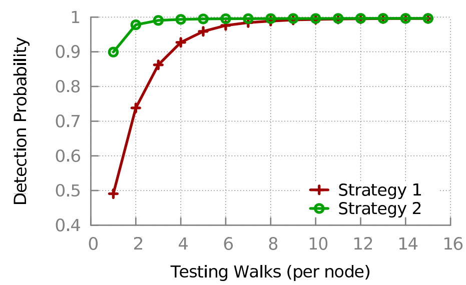


Fig. 6. Probability of detecting a route capture [Facebook wall post interaction graph]. The attack model includes 10 Sybils per attack edge.

and since the reduction of the number of attack edges reduces ϕ_F, it also leads to a reduction in the transient distribution of the random walk terminating at malicious nodes. Thus, it follows that a reduction in the number of remaining attack edges y_2 reduces the transient distribution of random walks terminating at malicious nodes. ∎

Figure 2 depicts the probability of random walks terminating at malicious nodes as a function of number of attack edges as well as the fraction of deleted edges when honest nodes use a global blacklisting policy. We can see that sacrificing attack edges so as to perform route capture attacks is a losing strategy for the attacker. Moreover, the decrease is similar for all random walk lengths; this is because even the stationary distribution of the random walk terminating at malicious nodes is reduced.

Anonymity Implication: To de-anonymize the user without the help of the destination node (e.g. the website to which the user connects anonymously), both the first hop and the last hop of the random walk need to be malicious to observe the connecting user and her destinations, respectively. End-to-end timing analysis [21], [61] makes it so that controlling these two nodes is sufficient for de-anonymization. Figure 4 depicts the probability of such an attack being successful as a function of the number of attack edges and the fraction of deleted edges using the global blacklisting policy. We can see that the probability of attack is a decreasing function of the fraction of deleted edges.Thus we conclude that route capture attacks are a losing strategy against our approach.

So far, we validated our analysis using simulations assuming an an ideal Sybil defense. We also validated our analysis using a more realistic Sybil defense that permits a bounded number (set to 10 [63]) of Sybils per attack edge, which we show in Figure 5.

B. Securing Reciprocal Neighborhood Policy

We now discuss the security and performance of our protocol that implements the reciprocal neighbor policy.

Security proof sketch: Suppose that a malicious node A aims to exclude an honest node B from its neighborlist. To pass node B's local integrity checks, node A has to return a neighborlist to node B that correctly advertises node B. Since random walks for anonymous communication are indistinguishable from testing random walks, there is a probability that the adversary will advertise a conflicting neighbor list that does not include node B to an initiator of the testing random walk. The initiator of the testing random walk will insert the malicious neighbor list into the Whanau DHT, and node B can perform a robust lookup for node A's key to obtain the conflicting neighbor list. Since Whanau only provides availability, node B can check for integrity of the results by verifying node A's signature. Since honest nodes never advertise two conflicting lists within a time interval, node B can infer that node A is malicious.

Performance Evaluation: We analyze the number of testing random walks that each node must perform to achieve a high probability of detecting a malicious node that attempts to perform a route capture attack. Nodes must perform enough testing walks such that a high percentage of compromised nodes (which are connected to honest nodes) have been probed in a single time slot. First, we consider a defense strategy where honest nodes only insert the terminal hop of the testing random walks in Whanau (*Strategy 1*). Intuitively, from the coupon collectors problem, $\log n$ walks per node should suffice to catch a malicious node with high probability. Indeed, from Figure 6, we can see that six testing walks per time interval suffice to catch a malicious node performing route capture attacks with high probability. The honest nodes can also utilize all hops of the testing random walks to check for conflicts (*Strategy 2*), in which case only two or three testing walks are required per time interval (at the cost of increased communication overhead for the DHT operations).

Next, we address the question of how to choose the duration of the time interval (t). The duration of the time slot

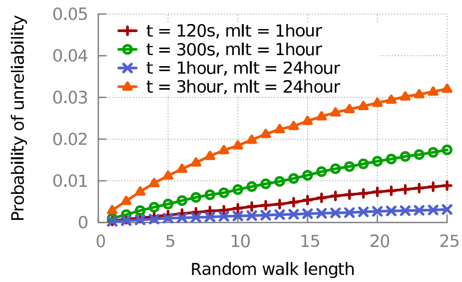


Fig. 7. Unreliability in circuit construction [Facebook wall post interaction graph].

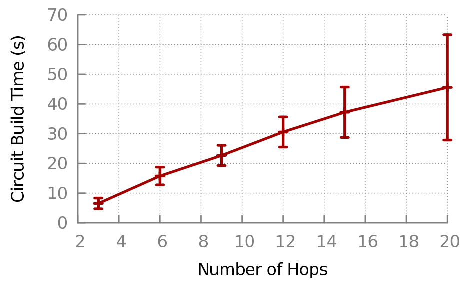


Fig. 8. Circuit build times in Tor as a function of circuit length

governs the trade-off between communication overhead and reliability of circuit construction. A large value of the time slot interval results in a smaller communication overhead but higher unreliability in circuit construction, since nodes selected in the random walk are less likely to still be online. On the other hand, a smaller value of the time interval provides higher reliability in higher circuit construction at the cost of increased communication overhead, since a fixed number of testing walks must be performed within the duration of the time slot. We can see this trade-off in Figure 7. We consider two churn models for our analysis: (a) nodes have a mean lifetime of 24 hours (reflecting behavior of Tor relays [27]), and (b) nodes have a mean lifetime of 1 hour (reflecting behavior of conventional P2P networks). For the two scenarios, using a time slot duration of 3 hours and one of 5 minutes, respectively, results in a 2-3% probability of getting an unreliable random walk for up to 25 hops.

Overhead: There are three main sources of communication overhead in our system. First is the overhead due to setting up the neighbor lists; which requires about d^2 KB of communication, where d is the node degree. The second source of overhead is the testing random walks, where nodes are required to perform about six such walks of length 25. The third source of overhead comes from participation in the Whanau DHT. Typically, key churn is a significant source of overhead in Whanau, requiring all of its routing tables to be rebuilt. However, in our scenario, only the values corresponding to the keys change quickly, but not the keys themselves, requiring only a modest amount of heartbeat traffic [28]. Considering the Facebook wall post topology, we estimate the mean communication overhead per node *per time interval* to be only about 6 MB. We also evaluate the latency of constructing long onion routing circuits through experiments over the live Tor network. We used the Torflow utility to build Tor circuits with varying circuit lengths; Figure 8 depicts our experimental results. Using these results, we estimate that 25 hop circuits would take about 1 minute to construct.

C. Anonymity

Earlier, we considered the probability of end-to-end timing analysis as our metric for anonymity. This metric considers the scenario where the adversary has exactly de-anonymized the user. However, in random walk based anonymous communication, the adversary may sometimes have probabilistic knowledge of the initiator. To quantify all possible sources of information leaks, we now use the entropy metric to quantify anonymity [12], [49]. The entropy metric considers the *probability distribution* of nodes being possible initiators, as computed by the attackers. In this paper, we will restrict our analysis to Shannon entropy, since it is the most widely used mechanism for analyzing anonymity. There are other ways of computing entropy, such as guessing entropy [31] and min entropy [50], which we will consider in the full version of this work. Shannon entropy is computed as:

$$H(I) = \sum_{i=0}^{i=n} -p_i \cdot \log_2(p_i) \tag{10}$$

where p_i is the probability assigned to node i of being the initiator of a circuit. Given a particular observation o, the adversary can first compute the probability distribution of nodes being potential initiators of circuits $p_i|o$ and then the corresponding conditional entropy $H(I|o)$. We can model the entropy distribution of the system as a whole by considering the weighted average of entropy for each possible observation, including the null observation.

$$H(I|O) = \sum_{o \in O} P(o) \cdot H(I|o) \tag{11}$$

We first consider the scenario where an initiator performs an l-hop random walk to communicate with a malicious destination, and the nodes in the random walk are all honest, i.e., the adversary is external to the system. For this scenario, we will analyze the expected initiator anonymity under the conservative assumption that the adversary has complete knowledge of the entire social network graph.

Malicious destination: A naive way to compute initiator entropy for this scenario is to consider the set of nodes that are reachable from the terminus of the random walk in exactly l hops (the adversary's observation), and assign a uniform probability to all nodes in that set of being potential initiators. However, such an approach does not consider the mixing characteristics of the random walk; l hop random walks starting at different nodes may in fact have heterogeneous probabilities of terminating at a given node.

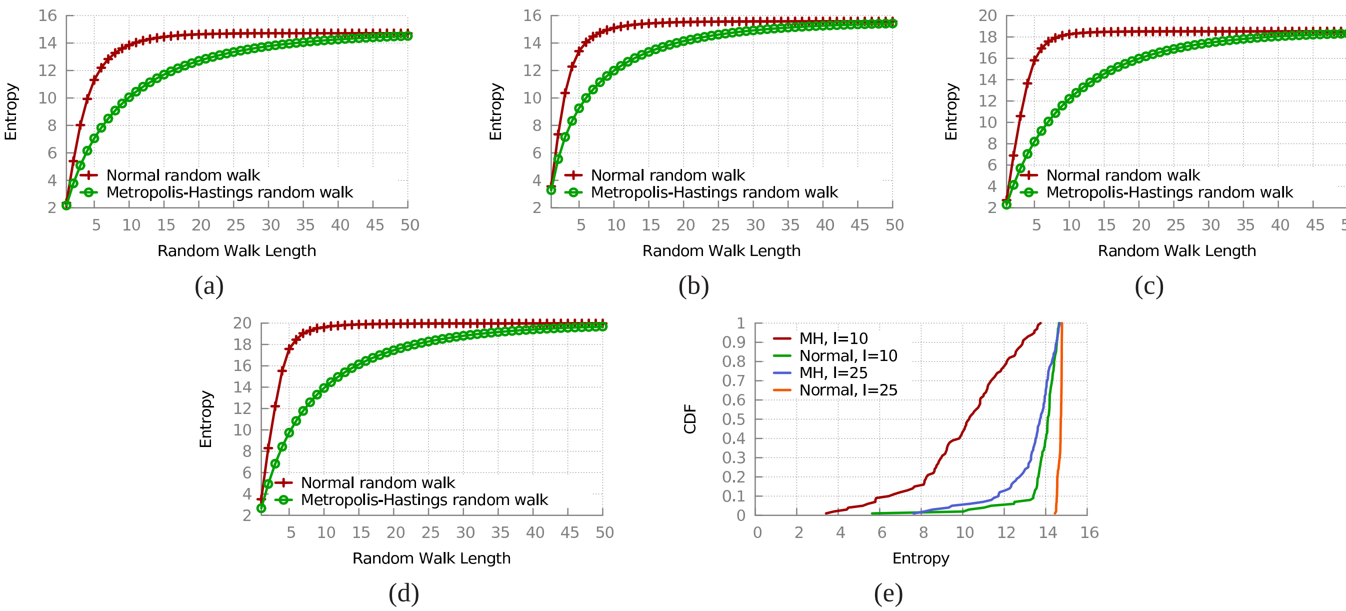


Fig. 9. *Expected entropy as a function of random walk length using (a) Facebook wall post graph (b) Facebook link graph (c) Anonymous Interaction graph (d) Anonymous link graph and (e) CDF of entropy for Facebook wall graph and malicious destination.*

We now outline a strategy that explicitly considers the mixing characteristics of the trust topology. Let the terminus of an l hop random walk be node j. The goal of the adversary is to compute probabilities p_i of a particular node being the initiator of the circuit:

$$p_i = \frac{P^l_{ij}}{\sum_x P^l_{xj}} \tag{12}$$

where P^l denotes the l-hop transition matrix for the random walk process. Note that even for moderate size social graphs, the explicit computation of P^l is infeasible in terms of both memory and computational constraints. This is because even though P is a sparse matrix, iterative multiplication of P by itself results in a matrix that is no longer sparse. To make the problem feasible, we propose to leverage the *time reversibility* of our random walk process. We have previously modeled the random walk process as a Markov chain (Theorem 2 in Appendix). Markov chains that satisfy the following property are known as time-reversible Markov chains [2].

$$\pi_i \cdot P_{ij} = \pi_j \cdot P_{ji} \tag{13}$$

Both the conventional random walk and the Metropolis-Hastings random walk satisfy the above property and are thus time-reversible Markov chains. It follows from time reversibility [2], that:

$$\pi_i \cdot P^l_{ij} = \pi_j \cdot P^l_{ji} \implies P^l_{ij} = \frac{\pi_j}{\pi_i} \cdot P^l_{ji} \tag{14}$$

Thus it is possible to compute P^l_{ij} using P^l_{ji}. Let V_j be the initial probability vector starting at node j. Then the probability of an l hop random walk starting at node j and ending at node i can be computed as the i'th element of the vector $V_j \cdot P^l$. Observe that $V_j \cdot P^l$ can be computed without computing the matrix P^l:

$$V_j \cdot P^l = (V_j \cdot P) \cdot P^{l-1} \tag{15}$$

Since P is a sparse matrix, $V_j \cdot P$ can be computed in $O(n)$ time, and $V_j \cdot P^l$ can be computed in $O(nl)$ time. Finally, we can compute the probabilities of nodes being potential initiators of circuits using equation (12), and the corresponding entropy gives us the initiator anonymity. We average the resulting entropy over 100 randomly chosen terminal nodes j to compute the expected anonymity.

Figure 9(a)-(d) depicts the expected initiator anonymity as a function of random walk length for different social network topologies. We can see that longer random walks result in an increase in anonymity. This is because for short random walks of length l in restricted topologies such as trust networks, not every node can reach the terminus of the random walk in l hops. Secondly, even for nodes that can reach the terminus of the random walk in l hops, the probabilities of such a scenario happening can be highly heterogeneous. Further more, we can see that conventional random walks converge to optimal entropy in about 10 hops for all four topologies. In contrast, the Metropolis-Hastings random walks used in Pisces take longer to converge. This is because random walks in Pisces have slower mixing properties than conventional random walks. However, we can see that even the Metropolis-Hastings random walk starts to converge after 25 hops in all scenarios.

To get an understanding of the distribution of the entropy, we plot the CDF of entropy over 100 random walk samples in Figure 9(e). We can see that the typical anonymity offered by moderately long random walks is high. For example, using a

Metropolis-Hastings random walk of length 25, 95% of users get an entropy of at least 11 bits. So far, we observed that Metropolis-Hastings random walks need to be longer than conventional random walks for equivalent level of anonymity against a malicious destination. Next, we will see the benefit of using Metropolis-Hastings random walks in Pisces, since they can be secured against insider attacks.

Insider adversary: We now analyze the anonymity of the system with respect to an insider adversary (malicious participants).We first consider an adversary that has g attack edges going to honest nodes, with $g = O(\frac{h}{\log h})$, and 10 Sybils per attack edge [63]. When both the first and the last hop of a random walk are compromised, then initiator entropy is 0 due to end-to-end timing analysis. Let M_i be the event where the first compromised node is at the ith hop and the last hop is also compromised. Suppose that the previous hop of the first compromised node is node A. Under this scenario, the adversary can localize the initiator to the set of nodes that can reach the node A in $i-1$ hops. If we denote the initiator anonymity under this scenario as $H(I|M_i)$, then from equation (11), it follows that the overall system anonymity is:

$$H(I|O) = \sum_{i=1}^{i=l} P(M_i) \cdot H(I|M_i) + (1 - \sum_{i=1}^{i=l} P(M_i)) \cdot \log_2 n \tag{16}$$

We compute $P(M_i)$ using simulations, and $H(I|M_i)$, using the expected anonymity computations discussed above. Figure 10(a) depicts the expected entropy as a function of the number of attack edges. We find that Pisces provides close to optimal anonymity. Moreover, as the length of the random walk increases, the anonymity does not degrade. In contrast, without any defense, the anonymity decreases with an increase in the random walk length (not shown in the figure), since at every step in the random walk, there is a chance of the random walk being captured by the adversary. At $g = 3000$, the anonymity provided by a conventional 10-hop random walk without any defenses (used in systems such as Drac and Whanau) is 14.1 bits, while Pisces provides close to optimal anonymity at 14.76 bit. For uniform probability distributions, this represents an increase in the size of the anonymity set by a factor of 1.6. It is also interesting to see that the advantage of using Pisces increases as the number of attack edge increases. To further investigate this, we consider the attack model with perfect Sybil defense and vary the number of attack edges. Figure 10(b) depicts the anonymity as a function of the number of attack edges. We can see that at 60 000 attack edges, the expected anonymity without defenses is 7.5 bits, as compared to more than 13 bits with Pisces (anonymity set size increases by a factor of 45).

Comparison with ShadowWalker: ShadowWalker [37] is a state-of-the-art approach for scalable anonymous communication that organizes nodes into a structured topology such as Chord and performs secure random walks on such topologies. We now compare our approach with ShadowWalker. To compute the anonymity provided by ShadowWalker, we use the fraction f of malicious nodes in the system as an input to the analytic model of ShadowWalker [37], and use ShadowWalker parameters that provide maximum security. Figure 11(a) depicts the comparative results between Pisces (using $l = 25$) and ShadowWalker. We can see that Pisces significantly outperforms ShadowWalker. At $g = 1000$ attack edges, Pisces provides about two bits higher entropy than ShadowWalker, and this difference increases to six bits at $g = 3000$ attack edges[1]. This difference arises because Pisces directly performs random walks on the social network topology, limiting the impact of Sybil attackers, while ShadowWalker is designed to secure random walks only on structured topologies. Arranging nodes in a structured topology loses information about trust relationships between users, resulting in poor anonymity for ShadowWalker. [2] For comparison, we also consider the attack model with perfect Sybil defense and vary the number of attack edges. Figure 11(b) depicts the results for this scenario. We can see that even in this scenario where trust relationships lose meaning since the adversary is randomly distributed, Pisces continues to provides comparable anonymity to ShadowWalker. Pisces's entropy is slightly lower since social networks are slower mixing than structured networks, requiring longer length random walks than ShadowWalker and thereby giving more observation points to the adversary.

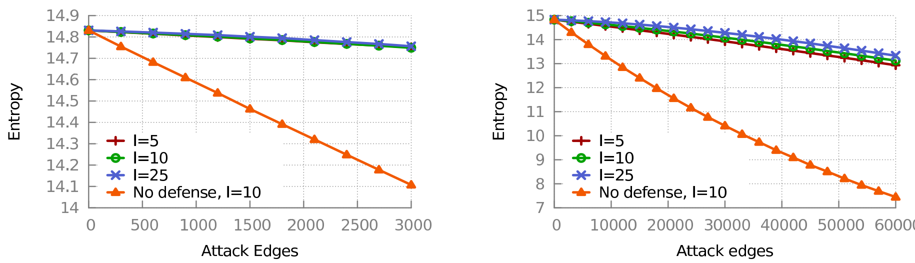
Performance optimization: We now analyze the anonymity provided by our two hop optimization, which uses the k-th hop and the last hop of the random walk for anonymous communication. To analyze anonymity in this scenario, let us redefine M_i ($i \neq k$) as the event when the first compromised node is at the i-th hop, the last node is also compromised, but the k-th node is honest. Let M_k be the event where the k-th hop and the last hop are compromised (regardless of whether other nodes are compromised or not) and the definition of M_l remains the same as before, i.e., only the last hop is compromised. We can compute system anonymity as:

$$\begin{aligned} H(I|O) = &\sum_{i=1}^{i=k-1} P(M_i) \cdot H(I|M_i) + \sum_{i=k+1}^{l} P(M_i) \cdot H(I|M_k) \\ &+ (1 - \sum_{i=1}^{i=l} P(M_i)) \cdot \log_2 n \end{aligned} \tag{17}$$

Figure 12 depicts the anonymity for our two hop optimization for different choices of k. We see an interesting trade-off here. Small values of k are not optimal, since even though the first hop is more likely to be honest, when the last hop is compromised, then the initiator is easily localized. On the

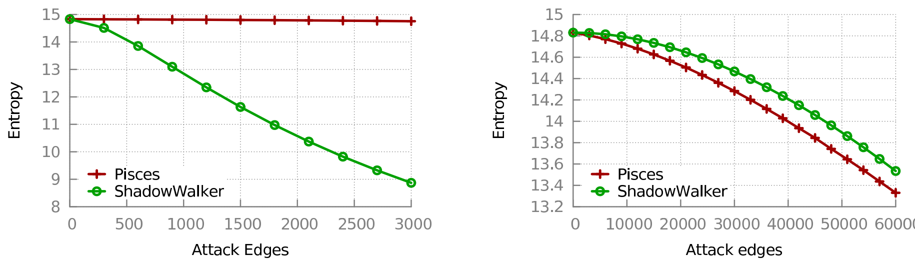
[1] At such high attack edges, ShadowWalker may even have difficulty in securely maintaining its topology, which could further lower anonymity.

[2] This observation is also applicable to Tor. Pisces provides 5 bits higher entropy than Tor at $g = 3000$ attack edges.



(a) (b)

Fig. 10. *Entropy as a function of fraction of attack edges using* (a) realistic model of an imperfect Sybil defense (10 Sybils per attack edge) and (b) perfect Sybil defense for Facebook wall post interaction graph. Note that the "No Defense" strategy models the random walks used in systems such as Drac and Whanau.



(a) (b)

Fig. 11. *Comparison with ShadowWalker. Entropy as a function of fraction of attack edges using* (a) realistic model of an imperfect Sybil defense (10 Sybils per attack edge) and (b) perfect Sybil defense for Facebook wall post interaction graph.

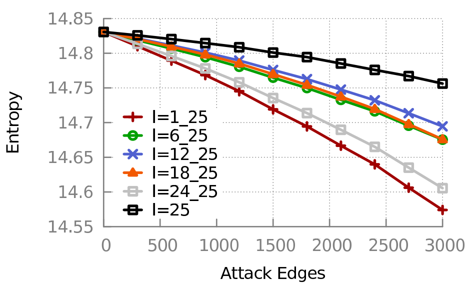


Fig. 12. Anonymity using the two hop performance optimization, Facebook wall graph, 10 Sybils/attack edge. $k = 12$ results in provides a good trade-off between anonymity and performance.

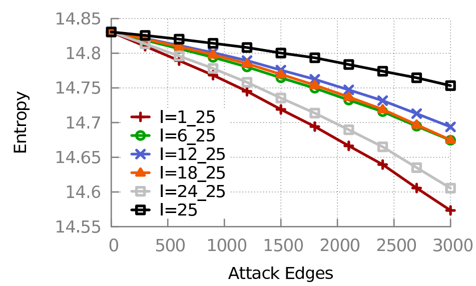


Fig. 13. Anonymity under the Selective DoS attack using the Facebook wall graph, 10 Sybils/attack edge. Selective DoS has limited impact.

other hand, large values of k are also not optimal, since these nodes are far away from the initiator in the trust graph and are less trusted. We find that optimal trade-off points are in the middle, with $k = 12$ providing the best anonymity for our optimization. We also note that the anonymity provided by our two hop optimization is close to the anonymity provided by using all 25 hops of the random walk.

Selective denial of service: Next, we evaluate Pisces anonymity against the selective DoS attack [5]. In this attack, an adversary can cause a circuit to selectively fail whenever he or she is unable to learn the initiator identity. This forces the user to construct another circuit, which results in a degradation of anonymity. We found that the degradation in initiator anonymity under this attack is less than 1%. The reason why Pisces is less vulnerable to selective DoS as compared with other systems such as Tor is due to the use of social trust. With high probability, most random walks traverse only the honest set of nodes. This result is illustrated in Figure 13.

Multiple communication rounds: So far, we had limited our analysis to a single communication round. Next, we analyze system anonymity over multiple communication rounds. Let us suppose that in communication rounds $1 \ldots z$, the adversary's observations are $O_1 \ldots O_z$. Let us denote a given node's probability of being the initiator after z communication rounds by $P(I = i|O_1, \ldots, O_z)$. Now, after communication round $z + 1$, we are interested in computing the probability $P(I = i|O_1, \ldots, O_{z+1})$. Using Bayes's theorem, we have that:

$$P(I = i|O_1, \ldots, O_{z+1}) = \frac{P(O_1, \ldots, O_{z+1}|I = i) \cdot P(I = i)}{P(O_1, \ldots, O_{z+1})} \tag{18}$$

The key advantage of this formulation is that we can now leverage the observations $O_1, \ldots O_{z+1}$ being independent

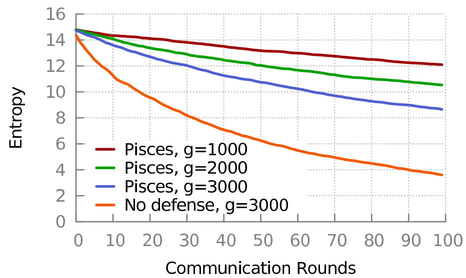


Fig. 14. Anonymity degradation over multiple communication rounds, Facebook wall graph, 10 Sybils/attack edge

given a choice of initiator. Thus we have that:

$$\begin{aligned}P(I=i|O_1,\ldots,O_{z+1}) &= \frac{\Pi_{j=1}^{j=z+1}P(O_j|I=i)\cdot P(I=i)}{P(O_1,\ldots,O_{z+1})}\\ &= \frac{\Pi_{j=1}^{j=z+1}P(O_j|I=i)\cdot P(I=i)}{\sum_{p=1}^{p=h}P(O_1,\ldots,O_{z+1}|I=p)\cdot P(I=p)}\\ &= \frac{\Pi_{j=1}^{j=z+1}P(O_j|I=i)\cdot P(I=i)}{\sum_{p=1}^{p=h}\Pi_{j=1}^{j=z+1}P(O_j|I=p)\cdot P(I=p)}\end{aligned} \tag{19}$$

Finally, assuming a uniform prior over all possible initiators, we have that:

$$P(I=i|O_1,\ldots,O_{z+1}) = \frac{\Pi_{j=1}^{j=z+1}P(O_j|I=i)}{\sum_{p=1}^{p=h}\Pi_{j=1}^{j=z+1}P(O_j|I=p)} \tag{20}$$

Figure 14 depicts the expected anonymity as a function of number of communication rounds. We can see that the entropy provided by Pisces outperforms conventional random walks by more than a factor of two (in bits) after 100 communication rounds (the anonymity set size is increased by a factor of 16).

V. Limitations and Future Work

While Pisces is the first decentralized design that can both scalably leverage social network trust relationships and mitigate route capture attacks, its architecture has some limitations. First, Pisces requires user's social contacts to participate in the system. To improve the usability of the system, in future work, we will investigate the feasibility of leveraging a user's two-hop social neighborhood in the random walk process. Pisces also does not preserve the privacy of users' social contacts. We emphasize that this is also a limitation shared by a large class of social network based systems, including Sybil defense mechanisms such as SybilLimit, SybilInfer and Whanau. Any distributed anonymity system relying on such Sybil defense mechanisms cannot preserve the privacy of users' social contacts.

Second, users who are not well connected in the social network topology may not benefit from using Pisces. This is because random walks starting from those nodes may take a very long time to converge to the stationary probability distribution (which provides optimal anonymity).

Third, Pisces does not defend against targeted attacks on an individual, in which the adversary aims to massively infiltrate or compromise the user's social circle for increasing the probability of circuit compromise. We note that the impact of such an attack is localized to the targeted individual.

Fourth, circuit establishment in Pisces has higher latency than existing systems, since random walks in Pisces tend to be longer. However, we note that circuits can be established pre-emptively, such that this latency does not affect the user. In fact, deployed systems such as Tor already build circuits pre-emptively.

Finally, Pisces currently does not support important constraints such as bandwidth-based load balancing and exit policies. The focus of our architecture was to secure the peer discovery process in unstructured social network topologies, and we will consider the incorporation of these constraints in future work.

VI. Conclusion

In this paper, we propose a mechanism for decentralized anonymous communication that can securely leverage a user's trust relationships against a Byzantine adversary. Our key contribution is to show that appearance of nodes in each other's neighbor lists can be made reciprocal in a secure and efficient manner. Using theoretical analysis and experiments on real world social network topologies, we demonstrate that Pisces substantially reduces the probability of active attacks on circuit constructions. We find that Pisces significantly outperforms approaches that do not leverage trust relationships, and provides up to six bits higher entropy than ShadowWalker (5 bits higher entropy than Tor) in a single communication round. Also, compared with the naive strategy of using conventional random walks over social networks (as in the Drac system), Pisces provides twice the number of bits of entropy over 100 communication rounds. In conclusion, we argue that the incorporation of social trust will likely be an important consideration in the design of the next generation of deployed anonymity systems.

Acknowledgment

We would like to thank the attendees of HotPETs 2010 and USENIX HotSec 2010 for helpful comments. In particular, this work benefited from conversations with George Danezis, Aaron Johnson, and Paul Syverson. This work is sponsored in part by NSF CAREER Award, number CNS-0954133, and by award number CNS-1117866. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect those of the National Science Foundation.

References

[1] Tor blog. https://blog.torproject.org/blog/tor-project-infrastructure-updates.

[2] D. Aldous and J. A. Fill. Reversible Markov chains and random walks on graphs. http://www.stat.berkeley.edu/∼aldous/RWG/book.html.

[3] O. Berthold, H. Federrath, and S. Köpsell. Web mixes: a system for anonymous and unobservable internet access. In *International workshop on Designing privacy enhancing technologies: design issues in anonymity and unobservability*, 2001.

[4] L. Bilge, T. Strufe, D. Balzarotti, and E. Kirda. All your contacts are belong to us: automated identity theft attacks on social networks. In *WWW*, 2009.

[5] N. Borisov, G. Danezis, P. Mittal, and P. Tabriz. Denial of service or denial of security? *ACM CCS*, 2007.

[6] Y. Boshmaf, I. Muslukhov, K. Beznosov, and M. Ripeanu. The socialbot network: when bots socialize for fame and money. In *ACSAC*, 2011.

[7] P. Boucher, A. Shostack, and I. Goldberg. Freedom systems 2.0 architecture. White paper, Zero Knowledge Systems, Inc., 2000.

[8] J. Boyan. The anonymizer: Protecting user privacy on the web. *Computer-Mediated Communication Magazine*, 4(9), 1997.

[9] G. Danezis, C. Diaz, C. Troncoso, and B. Laurie. Drac: an architecture for anonymous low-volume communications. In *PETS*, 2010.

[10] G. Danezis, C. Lesniewski-Laas, M. F. Kaashoek, and R. Anderson. Sybil-resistant DHT routing. In *ESORICS*, 2005.

[11] G. Danezis and P. Mittal. Sybilinfer: Detecting Sybil nodes using social networks. In *NDSS*, 2009.

[12] C. Diaz, S. Seys, J. Claessens, and B. Preneel. Towards measuring anonymity. In *PETS*, 2002.

[13] R. Dingledine, N. Mathewson, and P. Syverson. Tor: The second-generation onion router. In *USENIX Security*, 2004.

[14] J. Douceur. The Sybil Attack. In *IPTPS*, 2002.

[15] H. Federrath. Project: An.on - anonymity.online: Protection of privacy on the internet. http://anon.inf.tu-dresden.de/index_en.html.

[16] M. J. Freedman and R. Morris. Tarzan: A peer-to-peer anonymizing network layer. *ACM CCS*, 2002.

[17] E. Gilbert and K. Karahalios. Predicting tie strength with social media. In *CHI*, 2009.

[18] D. Goodin. Tor at heart of embassy passwords leak. *The Register*, September 10 2007.

[19] W. K. Hastings. Monte carlo sampling methods using markov chains and their applications. *Biometrika*, 57(1), 1970.

[20] C.-Y. Hong, C.-C. Lin, and M. Caesar. Clockscalpel: Understanding root causes of Internet clock synchronization inaccuracy. In *PAM*, 2011.

[21] A. Houmansadr, N. Kiyavash, and N. Borisov. Rainbow: A robust and invisible non-blind watermark for network flows. In *NDSS*, 2009.

[22] I2P. I2P anonymous network. http://www.i2p2.de/index.html, 2003.

[23] D. Irani, M. Balduzzi, D. Balzarotti, E. Kirda, and C. Pu. Reverse social engineering attacks in online social networks. In *DIMVA*, 2011.

[24] A. Johnson and P. Syverson. More anonymous onion routing through trust. In *IEEE CSF*, 2009.

[25] A. Johnson, P. F. Syverson, R. Dingledine, and N. Mathewson. Trust-based anonymous communication: adversary models and routing algorithms. In *ACM CCS*, 2011.

[26] R. Kannan, S. Vempala, and A. Vetta. On clusterings: Good, bad and spectral. *J. ACM*, 51(3), 2004.

[27] J. B. Kowalski. Tor network status. http://torstatus.blutmagie.de/.

[28] C. Lesniewski-Laas and M. F. Kaashoek. Whanaungatanga: A Sybil-proof distributed hash table. In *NSDI*, 2010.

[29] R. Levien and A. Aiken. Attack-resistant trust metrics for public key certification. In *USENIX Security*, 1998.

[30] B. N. Levine, M. Reiter, C. Wang, and M. Wright. Timing analysis in low-latency mix systems. In *FC*, 2004.

[31] J. L. Massey. Guessing and entropy. In *IEEE ISIT*, 1994.

[32] J. McLachlan, A. Tran, N. Hopper, and Y. Kim. Scalable onion routing with torsk. *ACM CCS*, 2009.

[33] N. Metropolis, A. W. Rosenbluth, M. N. Rosenbluth, A. H. Teller, and E. Teller. Equation of state calculations by fast computing machines. *The Journal of Chemical Physics*, 21(6), 1953.

[34] D. L. Mills. *Computer Network Time Synchronization: The Network Time Protocol*. CRC Press, 2006.

[35] A. Mislove, G. Oberoi, A. Post, C. Reis, P. Druschel, and D. S. Wallach. AP3: Cooperative, decentrialized anonymous communication. *ACM SIGOPS European Workshop*, 2004.

[36] P. Mittal and N. Borisov. Infomation leaks in structured peer-to-peer anonymous communication systems. *ACM CCS*, 2008.

[37] P. Mittal and N. Borisov. Shadowwalker: Peer-to-peer anonymous communication using redundant structured topologies. *ACM CCS*, 2009.

[38] P. Mittal, N. Borisov, C. Troncoso, and A. Rial. Scalable anonymous communication with provable security. In *USENIX HotSec*, 2010.

[39] P. Mittal, M. Caesar, and N. Borisov. X-vine: Secure and pseudonymous routing using social networks. In *NDSS*, 2012.

[40] P. Mittal, F. Olumofin, C. Troncoso, N. Borisov, and I. Goldberg. PIR-Tor: Scalable anonymous communication using private information retrieval. In *USENIX Security*, 2011.

[41] S. Nagaraja. Anonymity in the wild: mixes on unstructured networks. In *PETS*, 2007.

[42] A. Nambiar and M. Wright. Salsa: A structured approach to large-scale anonymity. *ACM CCS*, 2006.

[43] A. Panchenko, S. Richter, and A. Rache. NISAN: Network information service for anonymization networks. *ACM CCS*, 2009.

[44] A. Pfitzmann and M. Hansen. A terminology for talking about privacy by data minimization: Anonymity, unlinkability, undetectability, unobservability, pseudonymity, and identity management. http://dud.inf.tu-dresden.de/literatur/Anon_Terminology_v0.34.pdf, Aug. 2010. v0.34.

[45] M. Reiter and A. Rubin. Crowds: Anonymity for web transactions. *ACM TISSEC*, 1(1), June 1998.

[46] M. Rennhard and B. Plattner. Introducing MorphMix: Peer-to-peer based anonymous internet usage with collusion detection. *WPES*, 2002.

[47] A. Rowstron and P. Druschel. Pastry: scalable, decentralized object location and routing for large-scale peer-to-peer systems. In *MIDDLEWARE*, 2001.

[48] M. Schuchard, A. W. Dean, V. Heorhiadi, N. Hopper, and Y. Kim. Balancing the shadows. In *WPES*, 2010.

[49] A. Serjantov and G. Danezis. Towards an information theoretic metric for anonymity. In *PETS*, 2002.

[50] V. Shmatikov and M.-H. Wang. Measuring relationship anonymity in mix networks. In *ACM WPES*, 2006.

[51] I. Stoica, R. Morris, D. Liben-Nowell, D. R. Karger, M. F. Kaashoek, F. Dabek, and H. Balakrishnan. Chord: A scalable peer-to-peer lookup protocol for Internet applications. *IEEE/ACM Trans. Netw.*, 11(1):17–32, 2003.

[52] P. Syverson, G. Tsudik, M. Reed, and C. Landwehr. Towards an analysis of onion routing security. *Workshop on Design Issues in Anonymity and Unobservaility*, 2000.

[53] P. F. Syverson, D. M. Goldschlag, and M. G. Reed. Anonymous connections and onion routing. *Security & Privacy, IEEE*, 4-7, 1997.

[54] P. Tabriz and N. Borisov. Breaking the collusion detection mechanism of MorphMix. In *PETS*, 2006.

[55] The Tor Project. Tor metrics portal. http://metrics.torproject.org/.

[56] The Tor Project. Tor metrics portal: Users. https://metrics.torproject.org/users.html.

[57] The Tor Project. Who uses Tor. http://www.torproject.org/about/torusers.html.en.

[58] E. Vasserman, R. Jansen, J. Tyra, N. Hopper, and Y. Kim. Membership-concealing overlay networks. In *CCS*, 2009.

[59] B. Viswanath, A. Mislove, M. Cha, and K. P. Gummadi. On the evolution of user interaction in Facebook. In *WOSN*, 2009.

[60] Q. Wang, P. Mittal, and N. Borisov. In search of an anonymous and secure lookup. In *ACM CCS*, 2010.

[61] X. Wang, S. Chen, and S. Jajodia. Tracking anonymous peer-to-peer VoIP calls on the Internet. In *ACM CCS*, 2005.

[62] C. Wilson, B. Boe, A. Sala, K. P. Puttaswamy, and B. Y. Zhao. User interactions in social networks and their implications. In *Eurosys*, 2009.

[63] H. Yu, P. B. Gibbons, M. Kaminsky, and F. Xiao. Sybillimit: A near-optimal social network defense against Sybil attacks. In *IEEE S&P*, 2008.

[64] H. Yu, M. Kaminsky, P. Gibbons, and A. Flaxman. SybilGuard: Defending against Sybil attacks via social networks. In *SIGCOMM*, 2006.

[65] W. Yu, X. Fu, S. Graham, D. Xuan, and W. Zhao. DSSS-based flow marking technique for invisible traceback. In *IEEE S&P*, 2007.