

Let Your *CyberAlter* Ego Share Information and Manage Spam

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(Dated: October 14, 2021)

Almost all of us have multiple cyberspace identities, and these *cyberalter* egos are networked together to form a vast cyberspace social network. This network is distinct from the world-wide-web (WWW), which is being queried and mined to the tune of billions of dollars everyday, and until recently, has gone largely unexplored. Empirically, the cyberspace social networks have been found to possess many of the same complex features that characterize its real counterparts, including scale-free degree distributions, low diameter, and extensive connectivity. We show that these topological features make the latent networks particularly suitable for explorations and management via local-only messaging protocols. *Cyberalter* egos can communicate via their direct links (i.e., using only their own address books) and set up a highly decentralized and scalable message passing network that can allow large-scale sharing of information and data. As one particular example of such collaborative systems, we provide a design of a spam filtering system, and our large-scale simulations show that the system achieves a spam detection rate close to 100%, while the false positive rate is kept around zero. This system of letting *cyberalter* egos network among themselves has several advantages over other recent proposals for collaborative spam filtering: (i) It *uses an already existing network*, created by the same social dynamics that govern our daily lives, and no dedicated peer-to-peer (P2P) systems or centralized server-based systems need be constructed; (ii) It utilizes a *percolation search* algorithm (which can be viewed as mimicking how rumor is spread in a social network) that makes the query-generated traffic scalable; (iii) The network has a *built in trust system* (just as in social networks) that can be used to thwart malicious attacks; and (iv) It *can be implemented right now* as a plugin to popular email programs, such as MS Outlook, Eudora, and Sendmail.

I. INTRODUCTION

A. *CyberAlter* Ego and the Pervasive Cyberspace Social Networks

Our socioeconomic activities are getting intricately entwined with our identity in the cyberspace, and perhaps we are witnessing the emergence of an alter ego in the cyberspace. For example, every email user can construct a list of email addresses from which he has received emails or sent emails to; this constitutes one's *cyber-neighborhood*. This list is stored in the address books or contact lists managed by one's email client software or by the ISPs that one uses. It can be also automatically constructed by just sifting through one's mail box. Individuals on such lists have their own address books and contact links and soon there is a cyberspace network, in which our identities or *cyberalter* egos are firmly embedded and occupy various positions of power, centrality,

or proximity to cyber-communities of potential interest. Thus, an *undirected social email network* can be defined as follows: the nodes in the network correspond to email addresses; a pair of nodes is connected by an edge if a message is exchanged between the two nodes. Similarly, a *directed social email network* can be defined as follows: nodes also correspond to email addresses; a directed edge points from *A* to *B* if node *A* has sent an email to node *B* and vice versa[21]. One can modify this network to incorporate other parameters of interest; for example, each edge can be assigned a weight based on the number of email messages exchanged, or time-stamps can be added to messages along each edge so that one can prune the network to reflect the recent status of interactions among the *cyberalter* egos.

A major obstacle to studying such email networks has been that contact addresses and lists of a large enough group of *cyberalter* egos are not available in the public domain. Even though large ISPs, such as Hotmail, Yahoo, and AOL, have this information for all their users, they are not for public consumption. Drawn by the commercial potential of these latent networks, a number of companies [6] have started providing services where participants can upload their address books, allowing the corporation to create a central server where the social email network is stored and updated; the goal is to provide services to the participating clients by mining the

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network. These networks, however, are also proprietary, because of both privacy and commercial secrecy reasons. Fortunately for us (i) the system that *we have designed do not make use of the knowledge of the complete network*; to carry out the protocols described here, the *cyberalter* egos have only to exchange messages with those on their own contact lists and do not have to know about its cyber-neighbor lists, and (ii) A few examples of social email networks have been thoroughly studied in the literature, allowing us to observe that *they share many of the same complex features as* real world social networks. In particular, we will use the network analyzed by Ebel et al. in a recent work[11], which shows that the network has a scale-free structure, short diameter, and a giant connected component (*gcc*) that contains more than 95% of the nodes.

Since our *cyberalter* egos are becoming more entrenched as a significant part of our overall social and commercial selves, can one start managing and utilizing their network the same way that we manage our real-life social networks? Any such effort should abide by rules, such as the need to protect the privacy of the users and also the need to allow participants to dynamically decide whether they want to participate or not. The primary contribution of this paper is to *provide a decentralized, efficient, and scalable system for querying and sharing information on the global social networks*. One major application of this overlay information management system is to *filter spam*, as reviewed in the following.

B. Spam and Content-based Spam Filtering

Spam, or Unsolicited Bulk Email, is plaguing internet users around the world. It has been estimated that approximately 68% of the worldwide email traffic today is spam and up to 87% of the emails directed to US users is spam[3].

For the past few years, numerous spam filters have been proposed and deployed, and of all the existing anti-spam solutions, two classes of spam filters have emerged as the most effective and widely-deployed: *Bayesian/rule-based* spam filters and *collaborative* spam filters. A Bayesian filter uses the entire context of an e-mail in looking for words or phrases that will identify the e-mail as spam based on the experiences gained from the user's sets of legitimate emails and spams[12]. One example of a widely deployed Bayesian spam filter is SpamAssassin[4]. Although the Bayesian anti-spam solutions offer very impressive performances, they suffer from several serious drawbacks: first, Bayesian filters require an initial training period and exhibit a downgrade in performance for responding to messages composed of previously unknown words; second, Bayesian filters are unable to block messages that do not look like a typical spam such as messages that consist of only a URL or messages that are padded with random words. Most recently a number of multifaceted approaches have been

proposed[7, 17]. They consider combining various forms of filtering with infrastructure changes, financial changes, legal recourse, and more, to address shortcomings of regular statistical filters.

C. Collaborative Spam Filtering: Prior Work and Challenges

The increasing realization that the dynamic of spam constitutes a complex phenomenon brewed, fostered and propagated in the interconnected realm of the cyberspace, has prompted the use of collaborative spam filters, where the basic idea is to use the collective memory of, and feedback from, the users to reliably identify spams. That is, *for every new spam that is sent out, some user must be the first one to identify it* upon receiving this spam (e.g., by using a Bayesian filter or locally generated white and black lists); now, any subsequent user that receives an email that is a suspect, can query the community of email users to find out if it has been already tagged as spam or not. In contrast to Bayesian type filters, collaborative spam filters do not suffer from the drawbacks just mentioned above, and it has been shown that they are also capable of superior spam detection performance[22]. **The existing collaborative filtering schemes mostly ignore the already present and pervasive social communities in the cyberspace** and try to create new communities of their own to facilitate the sharing of information. This unenviable task of creating new social communities is beset with several difficulties that have limited the deployment and effective use of most collaborative filtering schemes proposed so far. The challenges include:

(i) *How to find users to participate?*: In order for a collaborative spam filter to be highly effective, a large number of users (on the order of hundreds of thousands or millions) must be participating in using the system. However, effectively finding and interconnecting a large number of willing participants is non-trivial. In other words making any artificially established community acceptable and popular is an unpredictable and difficult task at best, and impossible at worst.

(ii) *How to make the search scalable?*: The power of a collaborative spam filter lies in the fact that spam data resources from a large number of users are pooled together and utilized to fight spam. In order to avoid high server cost, the spam databases are typically stored locally on users' computer. Finding a way to do efficient searches on a network of distributed databases is very challenging.

(iii) *Who to trust?*: Inevitably, there would be malicious users who try to subvert the collaborative anti-spam system by providing false information regarding spam. Therefore, a trust scheme must be devised to place more weights on the opinions of some provably trustworthy users than on some unknown users who can be potentially malicious.

The different proposed schemes for collaborative filtering attempt to address the above challenges to different degrees of effectiveness. For example, SpamNet[5] employs the following mechanisms to address the challenges stated above: It *uses a central server model* to connect all the willing participants of this collaborative spam filter. *The central server solution is not scalable* as the system scales and the server becomes a single point of attack or failure. In addition, SpamNet employs a complicated algorithm to compute the trust score for each of its user. SpamWatch[20] is a totally distributed spam filter based on the Distributed Hash Table (DHT) system Tapestry[19]. SpamWatch addresses the three challenges of a collaborative spam filter in the following ways: First, SpamWatch uses a DHT-based P2P system to connect all the participants. The primary drawback in using a DHT for collaborative spam filtering purpose is that DHT's do not provide a natural platform to network existing databases, such as every email user's personal database of spams. Merging and mining existing sets of databases is very difficult if not impossible. Second, SpamWatch uses a hash-based mechanism called Approximate Text Addressing (ATA) to perform general query searches for spams. However, as seen in the description of the ATA algorithm, *supporting general query search in a DHT is very complex and involves expensive operations*. DHT's typically excel at exact-match lookups but does not perform well for application that needs to support general search queries such as in a collaborative spam filter. Lastly, SpamWatch does not offer any mechanism to address the trust issue. Most recently Gray *et. al.* have proposed CASSANDRA, a collaborative spam filter where the network is formed as clusters of trusted and similar peers. Finally a new reputation analysis have been proposed by Golbeck *et. al.* [13] where reputation relationships are inferred from the structure and are used as a method to score emails.

D. Harnessing The Global Social Email Network

Recently, Boykin and Roychowdhury investigated the notion of utilizing social network to do spam filtering[8]. In their work, it was shown that just by looking at the clustering coefficient of an email user's personal contact networks, their algorithm is able to achieve a spam detection rate of 53% *with zero false positives*. Although this algorithm is very attractive, it ignores the larger social email network and focuses only on a projection of it, as witnessed by an individual user, and it begs the questions whether the larger social email networks can be harnessed.

In this paper, we show that a high-performance, scalable and secure information management and query system can be overlaid on the social email networks, and provide a case study for collaborative spam filtering. The basic idea is the same as that of other proposed collaborative spam filters; however, instead of using special-

ized network, we use the latent social email network over which the queries and messages are exchanged. We show how *the three challenges outlined in the preceding discussions can be effectively addressed* using the topological properties of the underlying social email networks and *recent advances in complex networks theory*. **First**, no especially designed network has to be created for collaborative filtering. In fact, one of the main features of this system is that *all queries and communications are exchanged via email* through personal contacts, and that *no server or a traditional P2P system with TCP/IP connections is needed*. **Second**, we observe that social email networks correspond to Power-Law (PL) graphs[23] [11], with a PL coefficient around 2. Hence, *the underlying network naturally possesses a scale-free structure* that is a key hall-mark of many unstructured P2P systems that have organically grown for file-sharing on the Internet. One can then utilize a scalable global search system, namely the *percolation search algorithm*, recently proposed by Sarshar *et. al.* [18], on this naturally scale-free graph of social contacts to enable peers to exchange their spam signature data. **Third**, one can *harvest and utilize the trust that is embedded in the web of email contacts*. By regarding contact links as local measures of trust and using a distributed Singular-Value-Decomposition (SVD) algorithm, we can obtain a trust score called *mailtrust*. In fact, the famous Google PageRank[9] is computed in a similar fashion. **Finally**, the proposed system *can be implemented right now* as plugin to popular email programs, such as the MS Outlook.

We show via extensive simulations that the system is also *capable of delivering high performances while incurring minimal costs*. Under the assumption that there would be a large number of users (on the order of hundreds of thousands or millions), the system can offer a spam detection rate around 99%; in fact, the detection rate can reach close to 100% when the number of users approach the internet scale. At the same time, the number of false positives in our system can be tightly controlled to a level very close to zero. Meanwhile, *as the number of users of the system scales, the communication cost of the system would be kept at a sublinear scale and the memory storage cost would grow only at a logarithmic scale*. In addition, due to the fact that *no TCP/IP connection is required* and all communications in the system is done via background email exchanges, *less computational and networking burden would be placed on local computers*. Lastly, the system is designed to be secure and rigorously protective of users' privacy and confidentiality.

The rest of the paper is organized as follows. In section II, we present the background theory and the important concepts vital to this paper, such as email network theory and the percolation search algorithm. In section III, we describe the protocol of our social network based collaborative anti-spam system in detail. In section IV, we use a real world email network to perform large-scale simulations of the system. In section V, we construct a

threat model and show by simulation that a social network based trust scheme is effective in minimizing damages caused by malicious users. Finally, in section VI, we address several important topics such as the protection of privacy and the system’s resilience against random user failure.

II. BACKGROUND CONCEPTS

Our system is motivated by a number of recent advances in *complex networks theory and systems*, Eigen-methods based computation of trust and relevance, and the proven efficacy of the spam digest system as signatures of emails. We briefly review this background material in this section.

A. Topology of Social Email Networks

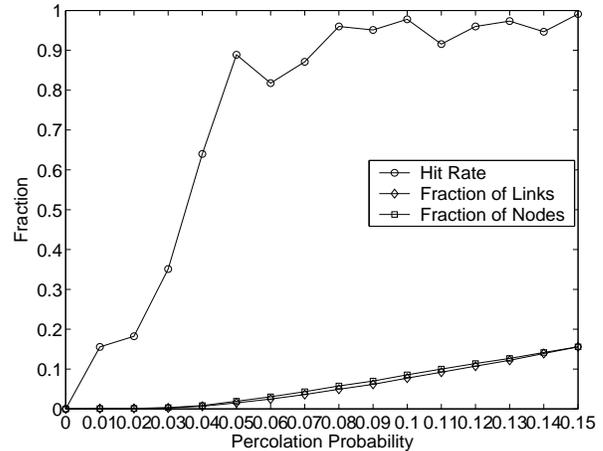
A particular email network comprising 56,969 nodes (i.e., email addresses) has been studied by Ebel et. al.[11] Based on the statistics reported in Ebel’s work, we identify three desirable properties that would make social email networks an attractive platform for building a collaborative spam filter:

(i) An email network has been found to possess a scale-free topology. More precisely, for the email network examined in [11], the node degree distribution follows a power law (PL): $P(k) \propto k^{-1.81}$, where k is the node degree, and $P(k)$ denotes the probability that a randomly chosen node has degree equal to k . One of the consequences of this property is that of very low percolation threshold[18]; in other words, *the network is extremely resilient to random deletions of nodes*. One can also show that even if high-degree nodes are deleted preferentially, *one has to remove almost all the high-degree nodes*, before the network gets fragmented.

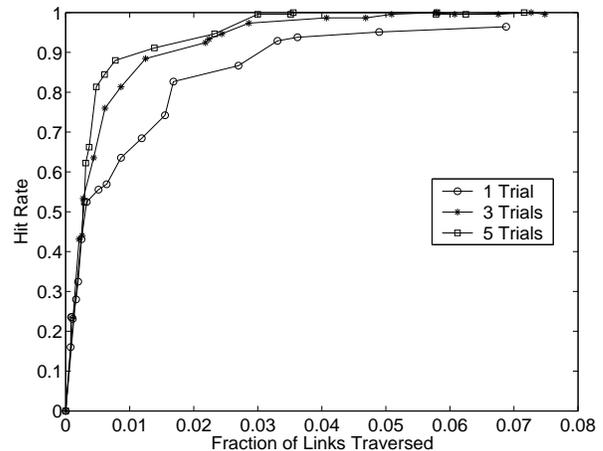
(ii) A large fraction of the nodes (95.2%) in a social email network is connected to the giant connected component (GCC). This means that any node can reach almost any other arbitrary node by simply following email links.

(iii) The email network has a low diameter (i.e. there exist short paths between almost any pair of two nodes in the network). In fact, for the email network investigated by Ebel et. al.[11], the mean shortest path length in the giant connected component was found to be $l = 4.95$ for a component size of 56,969 nodes. This short-diameter property allows any email user to efficiently communicate with any other email user in the network by crossing only a few email contact links.

The above properties of the social email network should not come as a surprise, since it reflects the same social dynamics that we practice in our everyday life.



(a)



(b)

FIG. 1: **Percolation Search On Social Email Networks:** (a) *The hit rate*, fraction of links and fraction of nodes traversed as a function of the percolation probability. Notice that there is a sudden jump in the hit rate above the percolation threshold, while the fraction of links and nodes processing the search query increases only linearly, after the threshold. The network used in this percolation search simulation is a real-world email contact network. The number of nodes is 56,969, $\tau \approx 1.81$, the TTL is 50 for both query and content implants and only one unique content exists in the network. (b) Hit rate for percolation search on email contact network with TTL of 50. *Repeating the percolation trial multiple times pushes the hit rate exponentially closed to 1.*

B. Percolation Search and Scalability

We can utilize the percolation search algorithm proposed by Sarshar et. al.[18] that exploits the presence of a tightly connected core comprising mostly high-degree nodes. In particular, *it is shown in [18] that unstructured*

searches in PL networks can be made highly scalable using the percolation search algorithm. The algorithm involves message passing on direct links only, and in some sense it resembles how rumors propagate in social networks. The key steps of the algorithm are as follows:

(i) *Caching or Content Implantation*: Each node performs a short random walk in the network and caches its content list on each of the visited nodes. The length of this short random walk is specified later and is referred to as the Time To Live (TTL).

(ii) *Query Implantation*: When a node intends to make a query, it first executes a short random walk of the same length as step 1 and implants its query requests on the nodes visited. The length of this random walk is usually taken to be the same as the TTL used in the content implantation process.

(iii) *Bond Percolation*: All the implanted query requests are propagated through the network in a probabilistic manner; upon receiving the query, a node would relay to each of its neighboring nodes with percolation probability p , which is a constant multiple of the percolation threshold, p_c , of the underlying network.

It is shown in [18] that the percolation threshold of any random network is given as $p_c = \langle k \rangle / \langle k^2 \rangle$. For a PL network with exponent τ and maximum degree k_{max} , we have $\langle k^2 \rangle = O(k_{max}^{3-\tau})$ and $\langle k \rangle = O(k_{max}^{2-\tau})$, and hence, we get a percolation threshold of $p_c = O(k_{max}^{-1})$, which is vanishingly small if k_{max} increases with the size of the network, which is usually the case. Thus, if we percolate at a multiple γ of p_c , then the total traffic generated would be, $C_\tau = \gamma p_c \langle k \rangle N = O(\frac{\langle k \rangle^2 N}{\langle k^2 \rangle}) = O(k_{max}^{-\tau+1} N)$. In real world networks, k_{max} typically scales sublinearly as a function of the network size. For $k_{max} = O(N^{1/\tau})$, we have: $C_\tau = O(k_{max}^{-\tau+1} N) = O(N^{\frac{1}{\tau}})$. For a detailed analysis of the hit rate and how it behaves as one performs multiple searches see [18].

Since the social email networks have a PL degree distribution, it is ideally suited for reaping the benefits of a percolation search, and the simulation plots obtained from performing percolation search on the real email dataset [1, 11] are provided in Fig. 1.

C. The MailTrust Algorithm

Just as in the case of WWW, where the PageRank captures the relevance of a particular web page, the topological structure of the social email networks can be used to assign trust or reputation to individual users. First, we model each email contact as placing a unit of trust on the recipient. Thus, for a node that contacts k_{out} other nodes, we can compute the fraction of trust that this node places on each of his out-neighbors as followed: the trust for neighbor i , t_i , is equal to the number of emails sent to neighbor i divided by the total number of emails sent. Note that the collection of t_i 's forms a probability vector, called the personal trust vector \vec{t} . Thus, if we model the entire email network as a discrete time Markov

chain, the local trust vector, \vec{t} , becomes the transition probability function for each node. We then compute the steady state probability vector using Power Iteration method which is the the same algorithm adopted to compute pagerank score of documents on web [9, 14]. As discussed in the literature, one needs to make sure that this Markov chain is ergodic and this can be achieved by having nodes with zero out-degree assign uniform trust to a set of pre-trusted nodes who have been carefully picked. An alternate way to compute the MailTrust score in a distributed fashion can be found in [14], along with a scheme on how the trust scores can be kept securely in the system even with the presence of malicious users.

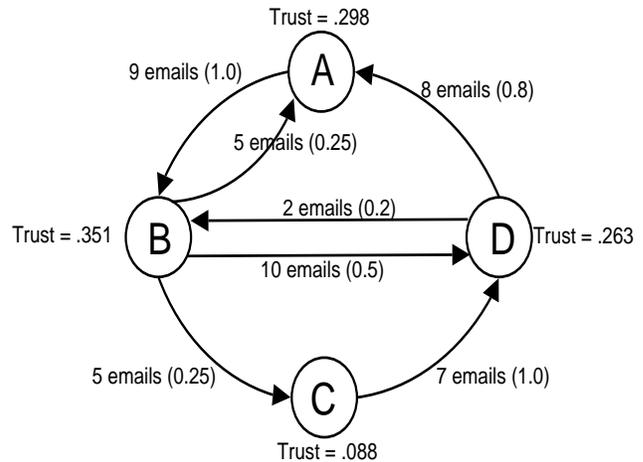


FIG. 2: **MailTrust**: A simple illustration of the MailTrust algorithm. The numbers in parentheses represent the local trust values that each node places on his/her neighbors. The MailTrust scores for each node is then obtained by computing steady state probability vector of the Markov chain.

We will refer to this trust score as *MailTrust* in the rest of this paper. A plot of the MailTrust scores obtained from [1, 11] is shown in Fig. 3.

D. Digest-based Spam Indexing

In a collaborative spam filtering system, it is important to have an effective mechanism to index known spams so that subsequent arrivals of the same spam can be correctly identified. The collaborative design of the system does not depend on any specific algorithm, but for initial experimental results we have adopted the well known *digest-based indexing* mechanism [10] to share spam information between users. Damiani et. al. have rigorously demonstrated that the digest algorithm described in [10] is highly resilient against the possible forms of automatic modifications of spam emails. The digest algorithm is further shown to satisfy both the privacy preserving and that it produces almost close to zero false positives (i.e., the digest of one email matches the digest of an unrelated email).

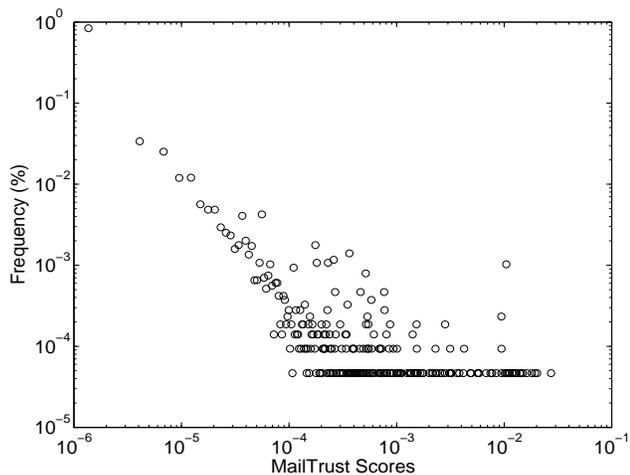


FIG. 3: **MailTrust Distribution:** The probability density function of MailTrust scores using 10^4 bins. These scores are obtained by applying the MailTrust algorithm on the email network data set from [11]. Notice that this probability density function is heavy-tailed, indicating that a few nodes are much more trustworthy than most nodes.

III. IMPLEMENTATION AND SYSTEM PROTOCOL

In order to use our proposed collaborative spam filtering system, an interested individual must first obtain a simple client program that works as a plug-in to an email program such as MS Outlook, Eudora, Sendmail, etc[24]. This simple client will only need to provide the following features: first, the client must come with a digest-generating function as specified in section IID; second, the client is responsible for keeping a personal blacklist of spams for the end-user as well as caching blacklists of spams for other nodes as described in the section on the percolation search algorithm, (see section IIB); third, the client would have access to the list of social email contacts (both inbound and outbound) of the end-user. The pseudo code of the distributed client is given in Algorithm 1.

Message Arrivals and Digest Indexing: When an email message arrives at the end-user, the method checks whether it is definitely spam or not spam (DefinitelySpam/DefinitelyNotSpam). Any traditional spam filtering method like white-list, blacklist, Bayesian filter, etc. can be integrated to create a hybrid multi tier architecture. *DefinitelyNotSpam* for example can be a white list of addresses in the contact list and *DefinitelySpam* can be output of a Bayesian filter when the filter indicates email as spam with very high probability. If an email is then suspected to be spam, the client program would call the digest function to generate a digest, D_e , for the message.

Making a Query in the System: Now, we would query the system to find out whether any other user in the network already has the digest, D_e , on its spam list.

Algorithm 1 PROCESS-MAIL(Email E)

```

1: if DefinitelySpam( $E$ ) then
2:   Mark  $E$  as Spam
3: else if DefinitelyNotSpam( $E$ ) then
4:   Mark  $E$  as not Spam
5: else
6:    $D_e = \text{Digest}(E); \{\text{Gray SPAM}\};$ 
7:   Implant percolation of  $D_e$  on a random walk of length  $l$ 
8:   Wait(T);
9:    $H_e = \text{HitScore}();$ 
10:  if  $H_e < \text{threshold}$  then
11:    Mark  $E$  as not Spam
12:  else
13:    Mark  $E$  as spam
14:  end if
15: end if

```

Algorithm 2 Publish-Spam(Email E)

```

1:  $D_e = \text{Digest}(E);$ 
2: Implant  $D_e$  on a random walk of length  $l$ 

```

Each query message for this digest is then implanted on a random walk of length l . Nodes with an implanted query request will then percolate the query message containing the digest, D_e , through their email contact network using a probabilistic broadcast scheme as specified in the *bond percolation* step of the percolation search algorithm. Each node visited by the query would declare a hit if the digest, D_e , matches with any of the digest that is cached on that node[25]. All the hits would be routed back to the node that originated the query through the same path that the query message arrives at the hit node. If the nodes have trust scores, then returned hits include the their trust score as well.

Processing the Hits and Making the Decision: After all the hits are routed back, *HitScore* is then calculated as (or as the weighted sum if using trust scheme; see Section IIC) sum of all the positive hits. If it exceeds a constant threshold value, the message in question is declared as spam; otherwise, the email message is determined to be non-spam.

Publishing Digest: If an email is declared as spam, and placed in the user's "spam" folder then the *Publish-Spam* function would be called that generates the digest of the spam message, D_e and caches the digest on a short random walk, as specified in the *caching or content implantation* step of the percolation search algorithm.

System Maintenance: If the EigenTrust algorithm

Algorithm 3 HitScore(Hits)

```

1: if Using MailTrust then
2:   HitScore =  $\sum_{h \in \text{Hits}} \text{mailtrust}(h)$ 
3: else
4:   HitScore =  $|\text{Hits}|$ 
5: end if
6: Return HitScore;

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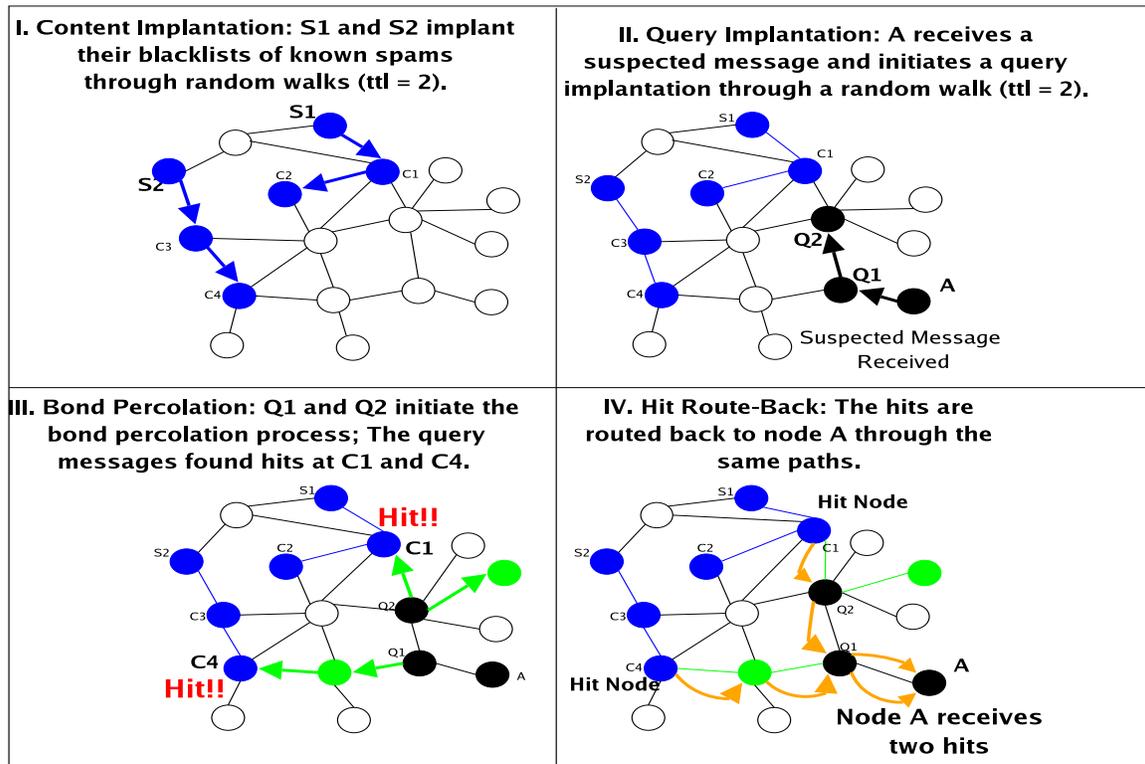


FIG. 4: An illustration of the protocol of the system.

from section II C is implemented, we would need to update the trust scores of the nodes on a periodic basis. Since most people’s amount of email contacts change not faster than a daily basis, The distributed EigenTrust computation should be performed at most once a day to obtain up to date trust scores for all nodes. Connectivity of the network is maintained by simple background message declaring join/leave sent to each of the user’s contacts.

IV. SIMULATION AND SYSTEM PERFORMANCE

Network Model: In this section, all simulations are performed on a real-world email network investigated in Ebel et.al.’s work[11]. (The email network data can be obtained via this url [1].) In the following simulations, only the *giant connected component* is used, which contains 95.2% of all nodes in the original dataset. Please see table I for the specific values of this email network’s parameters.

Spam Arrival Model: We model the spam detection performance of a collaborative spam filter as a function of the number of copies of the similar spam messages that arrive to the system. In the extreme case that every spam arrived to the system is unique, one can easily see that a collaborative filter would be totally futile, since no user can benefit from the prior identifications of others.

Assuming that similar spam messages are sent to approximately 5 million internet users on average[26] and estimating internet users to be 600 million worldwide[2]; thus, assuming that spammers select spam targets uniformly randomly from the set of all internet users, the probability that any individual would receive a copy of a given spam is approximately 0.8%. Since there are 56,969 nodes/users in our email network, the approximate number of identical spams arrived to this network is about 500. We further assume that each spam message arrives at nodes of the network uniformly randomly.[27]

Specification of Percolation Probabilities: Recall that in the percolation search algorithm, each edge gets a message with probability p which is chosen to be a constant multiple of the percolation threshold of the network. In general, the percolation threshold might not be known, and so one needs to come up with a scheme to adaptively perform the search using an increasing sequence of percolation probabilities. In order to ensure a high hit rate for queries and a low communication cost for the system, we propose the following scheme to perform query searches: we start the first query with very low percolation probability; if not enough hits are returned, we send out a second query with a percolation probability that is twice of the first one; if still not enough hits are routed back, we repeat the searches by increasing the percolation probability in this two-fold fashion until the probability value reaches a maximum value, p_{max} ; once this maximum is reached, we repeat the query with the

maximum percolation probability for a constant number of trials and stop. The query search is terminated as soon as the total number of distinct hits routed back reaches the threshold after any given trial. If *no hits are returned after n_{rep} attempts at the maximum probability p_{max}* , then the search is terminated and the queried item is considered as absent.

For the simulation experiment in this section, we set the starting percolation probability to be .00625 and p_{max} to be .05, and $n_{rep} = 3$. All other relevant parameters of the experiment are specified in Table I. In addition, we assume in this simulation experiment that upon the receipt of a new spam message, all nodes immediately cache this new content on a random walk as specified in the percolation search algorithm. This is done regardless of the fact that the spam has been automatically filtered by the system or it leaked through the filter and must be identified by human inspection or by some other means.

Simulation Execution: The simulation is repeated for 30 runs. In each run, 500 copies of the same spam arrive *sequentially* at different nodes in the network. The nodes are selected uniformly randomly for each spam message arrival. The first node receiving it performs a search, but of course gets 0 hits; similarly, the second node will also get at most one hit and it will be below the threshold of 2 to be identified as a spam. For the first two nodes, after the searches return no hits, the messages are manually tagged as spams. Since these two initial searches will be considered as misses, *the maximum detection rate is $498/500 = 99.6\%$* , where the detection rate is simply the number of successful spam detections divided by the total number of spam arrivals. We record the the detection rate for each run, compute the overall average and standard deviation, and plot the results in error-bar plots. In addition to the detection rate, we also record the percentage of edges crossed per query, which is the primary metric for network traffic cost. We repeat the simulation by varying one parameter: n_{reps} , which is the number of query trials repeated with percolation probability set at p_{max} before declaring failure.

Simulation Results Analysis: Fig. 5 plots the simulated spam detection rate (in percentage) as a function of n_{reps} , averaged over 30 runs. Note that for $n_{reps} \geq 3$, the spam detection rate is extremely close to the maximum detection rate of 99.6% for this experiment

Fig. 6, plots the percentage of edges crossed for per query as a function of n_{reps} , averaged over 30 runs. (A query is defined as a series of percolation search trials as defined in the subsection above.) Note that the network traffic cost is extremely low: on average, only approximately 0.1% of the 84,190 email links in the network needs to be crossed in order to get enough query hits to identify a suspected message as spam. Combining results from Fig. 5 and Fig. 6, one can argue that $n_{reps} = 3$ is a good operation point, since it gives near optimal spam detection performance while incurring minimal traffic cost.

Fig. 7 shows the network traffic as the average number of messages processed by nodes with degree k .

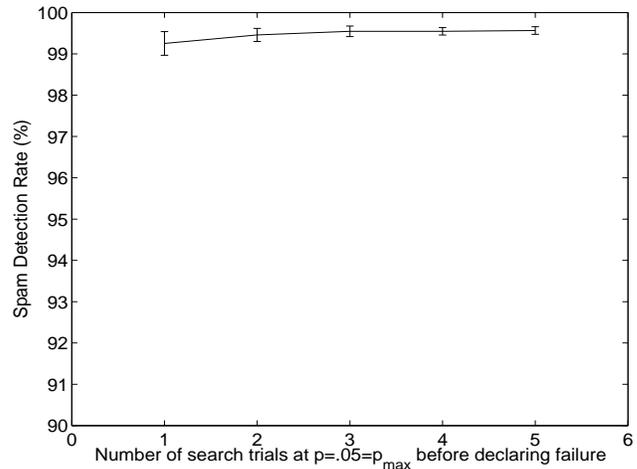


FIG. 5: **Spam Detection Performance:** This figure plots the simulated spam detection rate (in percentage) as a function of the number of query trials repeated with percolation probability set at p_{max} before declaring failure. Note that all the average detection rates are well above 99%. The results are averaged over 30 runs and the error bar plots one standard deviation above and below the mean.

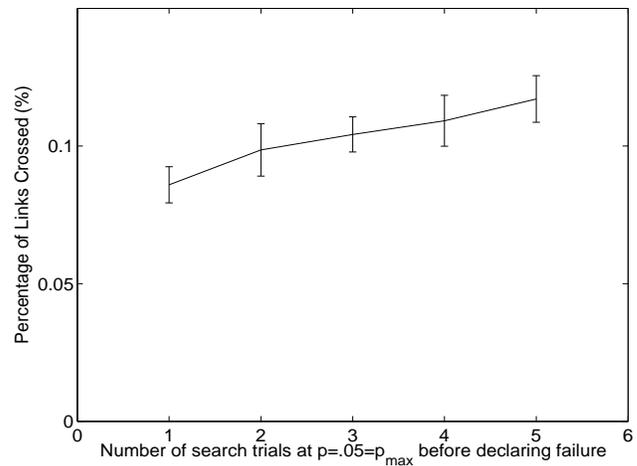


FIG. 6: **Overall Traffic Per Query:** This figure plots the percentage of edges crossed per query as a function of n_{reps} , average over 30 runs. Note that traffic cost is extremely low (only around 0.1% of network links need to be crossed per query). The error bar plots one standard deviation plus and minus the mean.

Fig. 8 shows the average number of participating nodes in a query as function of node degree. As expected that high-degree nodes are more likely to be visited for any given query since they are connected to a large number of nodes.

Bandwidth Cost Estimates: Fig. 6 shows that the required traffic for each query is about 0.1% of edges, which corresponds to about 84 emails. Moreover, every short email containing the digest of a message is about 1 KByte in size, and every email incurs band-

Network	# of nodes	56,969
	# of edges	84,190
	Node degree distribution	Power-Law (PL)
	PL exponent	≈ 1.8
	mean node degree $\langle k \rangle$	2.96
	node degree 2nd moment $\langle k^2 \rangle$	174.937
	approximate percolation threshold ($q_c \approx \frac{\langle k \rangle}{\langle k^2 \rangle}$)	.0169
	time-to-live (ttl)	50
Simulation Param.	# of arrivals of the same spam	500
	threshold (# of hits needed to identify spam)	2
	percolation probability trials	[.00625 .0125 .025 .05 .05 ...]
	# of runs	30
Threat Model	# of time steps	25
	# of malicious nodes inserted per time step	10
	total # of mailing lists	50,000
	Zipf coefficient	0.8
	# of non-spams queried per time step (x)	1,000
	m , number of items on a blacklist	10
	% of user's non-spam to be queried	5%

TABLE I: Simulation Settings

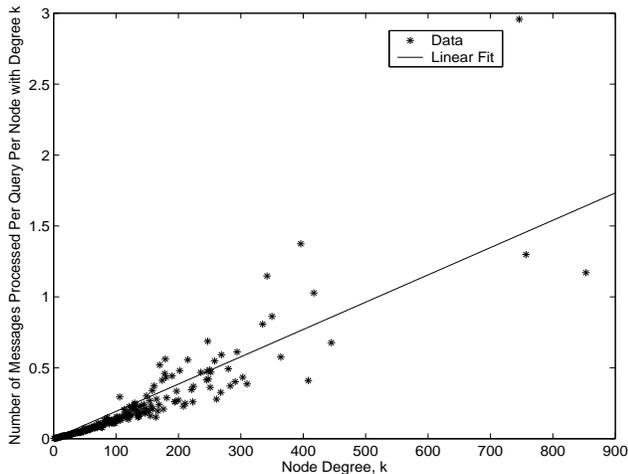


FIG. 7: **Traffic vs. Degree:** The data points show the average number of messages processed per percolation query for a node with degree k (i.e. it is the total number of messages processed per query for all nodes in the network with degree k divided by the number of nodes with degree k .) This plot is obtained by using an n_{reps} value of 3 for every percolation query. The slope of the linear fit is 0.0019 query/degree. since each node forwards a query to a link with a fixed percolation probability, we naturally expect that high-degree nodes handle more messages.

width cost on both the sender and receiver. Thus, the bandwidth cost per query is approximately $(84+50)$ email exchanges (where the number 50 corresponds to the random-walk query implantation with $TTL=50$), which at 1 KByte/email results in a total of 268 KByte per query. This total traffic per query is distributed among all the nodes, and in particular more among the high-degree nodes, as shown in Fig. 7.

Let us consider the worst case scenario first. In the

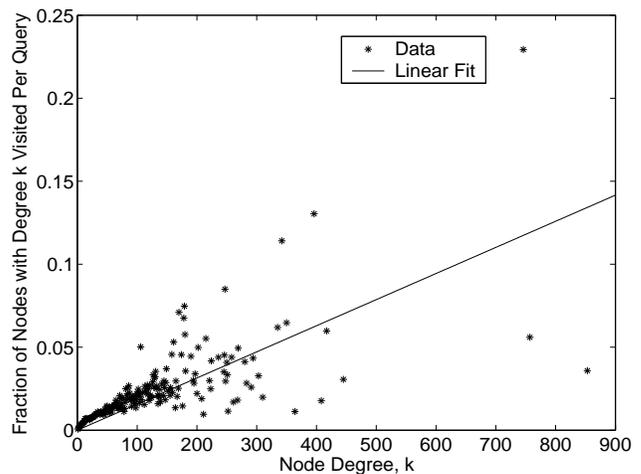


FIG. 8: The data points show the fraction of nodes with degree k visited per percolation query (i.e. it is the number of nodes with degree k visited per query divided by the total number of nodes in the network with degree k .) This plot is obtained by using an n_{reps} value of 3 for every percolation query. The slope of the linear fit is 1.573×10^{-4} /degree.

network used for this simulation, a very high-degree node typically processes around 1.5 messages per query in the network, as seen from Fig. 7; only one set of nodes uses more than this value. Assuming that every user gets 1 spam per hour, we conclude that a very high-degree node would need to process about 85,500 messages per hour since there are around 57,000 nodes in the network. Since the query message size is 1 KByte, the bandwidth cost on high degree nodes would be around 85 MByte per hour[28], which is equivalent to around 0.18 Mb/second. For a typical fast internet connection of 100 Mb/second, this represents about .2% of bandwidth cost.

For nodes with lower degree, *the cost is substantially lower*. For example, even a node with degree 100 would process on the average 0.19 messages per query, and hence, using the same estimate of 1 spam per node per hour, the bandwidth costs would be only around 23K/second.

V. THREAT MODEL AND EFFECTIVENESS OF TRUST SCHEME

In this section, we will construct a model of malicious users in the network trying their best to subvert the system. Through a large-scale simulation, we will demonstrate that implementing the EigenTrust algorithm presented in section II C can effectively reduce the damage inflicted by the malicious users.

With the system introduced so far, *a malicious node can subvert the system by introducing blacklists of well-known valid messages* into the network.[29] As a result, messages from mailing lists become easy targets of an attacker. Note that this form of attack will only raise the false positive rate of the system and it has no impact on the spam detection rate. Every malicious node will pick a fixed set of mailing lists and periodically update the blacklist with new messages from the mailing lists. In addition, it is assumed that the popularity of mailing lists follows a Zipf distribution and the probability that a mailing list is being queried follows the same Zipf law. We further assume that the spammer wants to inflict maximum damage and thus will select a given mailing list to blacklist following the same Zipf distribution for popularity since users of the system are more likely to be subscribed to popular mailing lists.

A. Simulation Setup and Trust Scheme

The simulation setup and parameters in this section will be identical to the simulation performed in section IV, except for the following: *first*, a small fraction of nodes in the network (250 nodes) will be labelled as malicious nodes and these malicious nodes will blacklist non-spams from popular mailing lists; *second*, for simulation purpose, we assume that the probability that a node in the email network is malicious is inversely proportional to its in-degree, since low in-degree nodes are trusted by a few peer email users and thus more likely to be malicious; *third*, the malicious nodes will follow all specifications of the protocol such as forwarding and routing queries, storing the cache implants for other nodes, etc.[30]; *fourth*, we relax the uniform spam arrival assumption in section IV. In this simulation, the probability that a node receives a spam is directly proportional to its in-degree. The justification for this assumption is that a high in-degree node signifies very active and long-time usage of the email account and thus more likely to receive spams. All relevant parameters are specified in Table I.

We then perform a Monte Carlo simulation on email network as follows: at every time step, ten malicious nodes would insert their malicious content, which consist of blacklists of non-spams; also, 500 copies of the same spam message arrive as in section IV; In addition to the spam arrivals, a constant number of non-spams would arrive and queried by users; based on the hits that are routed back, nodes would classify the messages queried to be spam or non-spam.

We will use two methods for spam classification: the *non-trust scheme* and the *MailTrust scheme* (for specification of the MailTrust algorithm, see section II C). Under the non-trust scheme, a suspected message is classified as spam if the number of distinct hits routed back is greater than or equal to a threshold (the threshold is set at 2 to give comparable performance as in section IV). For the MailTrust scheme, the queried message is identified to be spam if the sum of the MailTrust scores of the distinct hits routed back is above a threshold. This threshold is set to generate comparable spam detection rate as the non-trust scheme. The results are plotted in Fig. 9 for spam detection rate and false positive rate as a function of the number of malicious nodes inserted. As shown in the plot, the malicious nodes have no impact on the spam detection rate, since their blacklists of non-spams do not affect the ability of other normal users to blacklist and identify spams. From the spam detection rate plot, one can see that both schemes generate comparable spam detection rates. However, by examining the false positive rate plot, one can immediately see that *the MailTrust scheme results in about 50% improvement in lowering the false positive rate*.

The reason for this improvement is mainly due to the fact that high in-degree nodes tend to have high trust scores and receive more spams. Thus, for the MailTrust scheme, we can set the threshold value a little high and still have a very good spam detection rate, because a large fraction of query hits for spams will be provided by the high in-degree nodes who have high trust scores. In addition, most malicious nodes have low trust scores since they tend to have low in-degrees (this assumption is made in the subsection above).

VI. MISCELLANEOUS

A. Protection of Privacy

Since our proposed anti-spam system is social network based, it is very important to protect users' privacy by preventing anybody from using the network to map out social links. Furthermore, if a malicious individual is able to map out the social email network, a database of social contacts can be constructed to send out more spams from spoofed personal contacts. To address this problem, all messages exchanged in the system must be forwarded anonymously. The basic idea is that when a node forwards a message, any information pertaining to

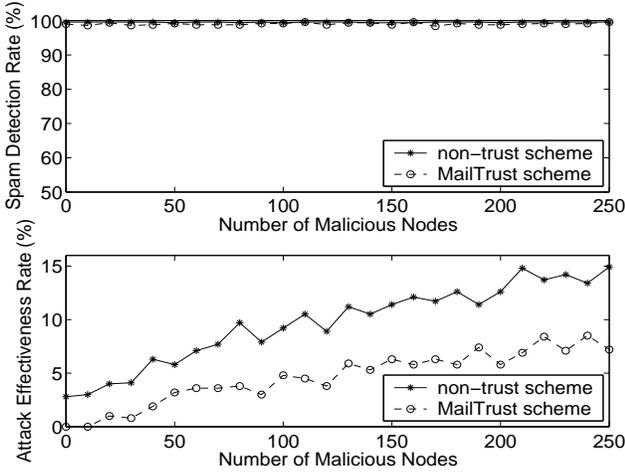


FIG. 9: **MailTrust Performance:** The top and bottom figures plot the spam detection rate and the attack effectiveness rate as a function of the number of malicious nodes that have joined the system. While both schemes yield approximately the same detection rate, the MailTrust scheme results in a significantly lower attack effectiveness rate. Note that we are assuming it is easy for malicious nodes to know of messages (e.g., sent to mailing lists) that a large number of nodes will receive. Clearly, incorporating a white-list based scheme for processing messages from mailing lists at the level of a *cyberalter ego*, would be the best way of handling such attacks.

which nodes that the message has visited must be deleted before forwarding. This keeps all system communications to an acquaintance-acquaintance level, Fig. 10.

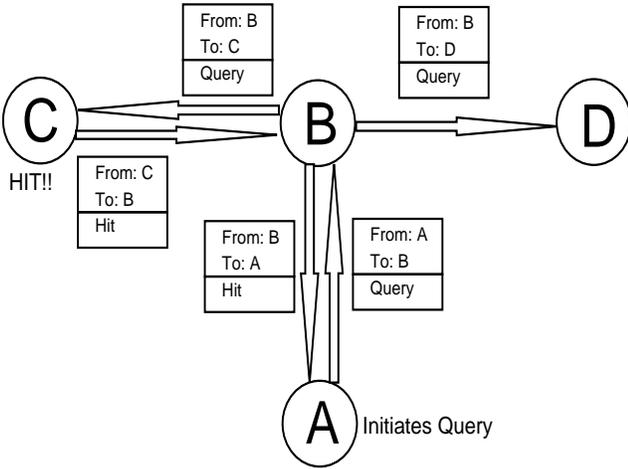


FIG. 10: **Protecting Privacy:** A simple diagram illustrating the secure version of message forwarding in the system. For example, note that both node C and node D do not know that the query comes from node A; similarly, node A does not know that the hit comes from node C.

B. System Resilience against User Unreliability

The users of the system are dynamic. Namely, users will logon and logoff as they wish. Since our system heavily relies on the underlying social email network, the natural question will be: how many users in the system can be offline before the network is severely segmented into many small components?

Alternately, we can re-phrase the above problem as followed: how many nodes in a network can randomly fail before the network becomes fragmented? It turns out that this problem has been extensively studied analytically and numerically [15, 16]. Using site percolation theory, Cohen et.al. [16] shows that scale-free PL networks are extremely robust to random failures: for a PL network with PL exponent less than 3, the critical fraction of nodes, p_c , that needs to be removed for the network to fragment goes to 1 as the network size approaches infinity. Furthermore, for a finite-size network with a large number of nodes on the order of tens of thousands, the critical fraction p_c is well over 0.99. Since the social email network is a PL network with exponent close to 2, these results from site percolation theory is directly applicable.

Therefore, the network will not be fragmented even if a massive number of system users suddenly leave. Alternately, one only needs a very small fraction of the users to be using the system before they can start successfully exchanging information.

C. Simple Measures for Performance Improvement

Spam Traps. When our proposed system is deployed in the real world, the initial number of users will be small. In fact, all collaborative spam filters must overcome this "initial hurdle" in order to become widely-used.

Our proposed solution to this "initial hurdle" problem is to install *spam traps*. By definition, a spam trap is an email account created for the sole purpose of attracting spams. These spam trap addresses can be easily promoted throughout the internet to attract a large number of spams. It has been noted by a commercial anti-spam company that only a few hundred well-spread spam traps are needed to catch almost all new spams [31]. These spam traps are not difficult to initiate and they do not cost much in bandwidth and memory storage to maintain. With spam traps properly installed, the system is ready to be deployed and offer superior spam detection performance.

Hybrid and Multi Tier Design. As discussed in section V, legitimate emails from popular mailing lists can easily become blacklist targets of the malicious users of the system. In addition to the trust scheme we proposed in section II C, any traditional spam filtering technique can be utilized as *DefinitelySpam* and *DefinitelyNotSpam* function in Algorithm 1 to achieve enhanced performance, and plug security holes in the collaborative system.

VII. CONCLUDING REMARKS

Our fairly comprehensive simulation results show that global social email networks possess several properties that can be exploited using *recent advances in complex networks theory* (e.g., the percolation search algorithm) to provide an efficient collaborative spam filter. Clearly, the proof-of-concept system discussed here can be vastly improved and augmented with schemes that have proven successful at various levels. Moreover, there is nothing special about searching for and caching spam digests, and one can use our pervasive message passing system for managing a general distributed information system. The primary requirement is to be able to provide enough benefits to the users so that they are motivated to cooperate, which is relatively easily accomplished when it comes to spam management. If users get used to the

spam filtering system, then we envision that queries for other information will follow.

The study brings out several aspects of the burgeoning cyberspace networks, and the increasingly powerful *Cyberalter ego*: (i) They have some of the same characteristics as their real-life counterparts, and hence, can be managed and explored using well-studied schemes; (ii) In many P2P applications, we do not need to explicitly define new links and form the network from scratch, but existing cyberspace and social contacts can be exploited as an efficient P2P infrastructure. Such existing networks combined with efficient tools, borrowed from the field of complex networks, can achieve almost optimum performance. This work and similar recent concepts [8] constitute some of the first steps toward the management and design of efficient and naturally grown collaborative systems in the cyberspace.

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 - [21] In this paper, we use the term social email network in the sense of an undirected network, except when we discuss the computation of trust.
 - [22] SpamNet[5], a fairly popular commercial collaborative anti-spam system, claims that a detection rate closed to 100 % and a false positive rate closed to 0 % are achieved.
 - [23] For a power-law (PL) degree distribution, the probability of a randomly chosen node to have degree k scales as $P(k) \propto k^{-\gamma}$ for large k ; γ is referred to as the exponent of the distribution.
 - [24] However, implementing the client program as an email program plug-in is not the only option; large email providers can also implement this system on the email server ends.
 - [25] Please refer to Damiani et. al.'s work [10] on the definition of matching digests.
 - [26] No statistics on this has been found but several online sources suggest that spammers usually send out on the order of millions of copies per unique message.
 - [27] We will see that in section V, this uniform assumption is relaxed. In fact, when no trust scheme is implemented, the selection of spam target node has no impact on spam detection performance since all contents are almost surely to be found with probability exponentially closed to one.

- [28] In this calculation, the bandwidth cost due to content caching and the routing back of messages is ignored.
- [29] There are other possible forms of attack such as a Denial-of-Service attack on the high-degree nodes by artificially flooding the network with queries. These forms of attacks are outside the scope of this paper.
- [30] Malicious nodes can undermine the performance of the system by failing to follow the protocol. However, this is outside the scope of the paper.
- [31] http://www.esafe.com/pdf/esafe/esafe_antispam_whitepaper.pdf