Improving Spam Detection Based on Structural Similarity

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Abstract

We propose a new spam detection algorithm that uses structural relationships between senders and recipients of email as the basis for spam detection. A unifying representation of users and receivers in the vectorial space of their contacts is constructed, that leads to a natural definition of similarity between them. This similarity is then used to group email senders and recipients into clusters. Historical information about the messages sent and received by the clusters is obtained by forwarding messages to an auxiliary spam detection algorithm and this information is used to reclassify messages. In the framework proposed, our algorithm aims at correcting misclassifications from an auxiliary algorithm. A simulation is performed based on actual data collected from an SMTP server from a large University. We show that our approach is able reduce false positives, produced by the auxiliary classification algorithm, up to about 60%.

1 Introduction

The relentless rise in spam email traffic, now accounting for about 83% of all incoming messages, up from 24% in January 2003 [14], is becoming one of the greatest threats to the use of email as a form of communication. Spam is also increasingly at the root of major security breaches as more viruses, worms and other malicious software makes use of spam messages to spread throughout the Internet.

A major problem in detecting spam stems from active adversarial efforts to thwart classification. Spam senders use a multitude of techniques based on knowledge of current algorithms, to evade detection. These techniques range from changes in the way text is written to frequent changes in elements, such as user names, domains, subjects, etc. Although such evasion strategies are usually naturally understood by humans, it is hard to automatically analyze them.

A central question that remains unanswered is: what are the identifiers of spam that are most costly to change, from the point of view of the spammer? The limitations of attempts to recognize spam by analyzing content are emphasized in [7]. Content-based techniques [15, 22, 16] have to cope with the constant changes in the way spammers generate their solicitations. The structure of the target space for these solicitations tends, however, to be much more stable since spam senders still need to reach recipients in order to be effective. Specifically, by structure we mean the space of recipients targeted by a spam sender, as well as the space of senders that targets a given recipient, i.e. the contact lists of a user. The contact lists, or subsets thereof, can then be thought of as a (dynamical) signature of spam senders and recipients. Additionally by constructing a similarity measure in these spaces we can track how lists evolve over time, by addition or removal of addresses.

In this paper, we propose and evaluate an algorithm for improving spam detection that uses structural relationships between senders and recipients as the basis for the detection of spam messages. The algorithm works in conjunction with another spam classifier (hereafter called auxiliary algorithm), necessary to produce spam or legitimate mail tags on past senders and receivers, which in turn are used to infer new ones, through structural similarity. The key idea is that the set of distinct recipients that spammers and legitimate users send messages to, as well as the set of distinct senders from which users receive messages from (which, in both cases, we call *contact lists*), can be used as identifiers of senders and recipients in email traffic [19, 11, 12]. We show that the application of our structural algorithms over the auxiliary classifier's results leads to the correction of a number of misclassifications.

This paper is organized as follows: Section 2 presents the methodology used to handle email data. Our struc-

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tural algorithm is described in Section 3. We present the characteristics of the workload studied in section 4, as well as the classification results obtained with our algorithm over this data set. Related work is presented in Section 5 and conclusions and future work in Section 6.

2 Modeling Similarity Among Email Senders and Recipients

Our proposed spam detection algorithm exploits the structural similarities in groups of senders and recipients of email. This section introduces a unifying modeling framework of individual email users and a metric that captures the similarity between them.

Our basic assumption is that, in legitimate and spam traffics, users have a list of peers they often have contact with (i.e., they send/receive an email to/from), as can be seen in Section 4. In legitimate traffic, contact lists stem from social relationships. On the other hand, the lists created by spammers to distribute their solicitations are guided by business opportunities and, generally, do not reflect any form of social interaction. Contact lists certainly change over time. However, we expect them to be much less variable than other identifiers commonly used for spam detection, such as the presence of certain keywords in the email content or its size and encoding. In other words, we expect contact lists to be an effective basis for detecting spam.

We start by representing an email user as a vector in a multi-dimensional vectorial space created out of all possible contacts. We represent email senders and recipients separately. We then use vectorial operations (the normalized inner product in the sender/recipient spaces) to express the similarity among multiple senders/recipients. Finally, similarity is used to associate users into clusters. Note that the term email user is used throughout this work to denote any identification of an email sender/recipient (e.g., email address, domain name, SMTP relay, etc).

Let N_r be the number of distinct recipients. We represent a sender s_i as a N_r dimensional vector, $\vec{s_i}$, defined in the vectorial space of email recipients. The n-th dimension (representing recipient r_n) of $\vec{s_i}$ is defined as:

$$\vec{s_i}[n] = \begin{cases} 1, & \text{if } s_i \rightarrow r_n \\ 0, & \text{otherwise} \end{cases}, \qquad (1)$$

where $s_i \rightarrow r_n$ indicates that sender s_i has sent at least one email to r_n recipient.

Similarly, we define $\vec{r_i}$ as a N_s dimensional vector representing recipient r_i, where N_s is the number of distinct senders being considered. The n-th dimension of this vector is analogously set to 1 if recipient r_i has received at least one email from s_n.

We next define the similarity between two senders s_i and s_j as the cosine of the angle between their vectorial representation ($\vec{s_i}$ and $\vec{s_j}$). The cosine is a well known metric that has been successfully employed in several application areas, including document similarity in information retrieval systems [3, 20] and intrusion detection [21]. This similarity metric is computed as:

$$sim(s_i, s_j) = \frac{\vec{s_i} \circ \vec{s_j}}{|\vec{s_i}||\vec{s_j}|} = cos(\vec{s_i}, \vec{s_j}), \qquad (2)$$

where $\vec{s_i} \circ \vec{s_j}$ represents the internal product of the vectors and $|\vec{s_i}|$ is the norm of $\vec{s_i}$. This metric varies between 0, when senders do not share any recipient in their contact lists, and 1, when senders have identical contact lists and thus have the same representation. The similarity between two recipients is similarly defined.

We note that our similarity metric has different interpretations in legitimate and spam traffics. In legitimate email traffic, it represents social relationships that consist of interactions with the same group of users, whereas in the spam traffic, a great similarity probably represents the use of different identifiers by the same spammer or the sharing of distribution lists by distinct spammers.

Finally, we can use our vectorial modeling approach to represent a cluster of senders or recipients. A sender cluster sc_i, represented by vector $\vec{sc_i}$, is computed as the vector sum of its elements, that is:

$$\vec{sc_i} = \sum_{s_j \in sc_i} \vec{s_j} \qquad (3)$$

The similarity between a sender s and an existing cluster sc_i can be assessed by extending Equation 2 as follows:

$$sim(sc_i, s) = \begin{cases} cos(\vec{sc_i} - \vec{s}, \vec{s}), & \text{if } s \in sc_i \\ cos(\vec{sc_i}, \vec{s}), & \text{otherwise} \end{cases} \qquad (4)$$

We note that the vectorial representation of a sender $\vec{s}$ and of the the sender's cluster may change over time as new emails are considered. In order to accurately estimate the similarity between a sender $\vec{s}$ and a sender cluster $\vec{sc_i}$ to which $\vec{s}$ currently belongs to, we first remove $\vec{s}$ from $\vec{sc_i}$, and then take the cosine between the two vectors ($\vec{sc_i} - \vec{s}$ and $\vec{s}$). This guarantees that the previous classification of a user does not influence its new classification. Recipient clusters and similarities are defined analogously.

3 Structural Similarity Algorithm

This section introduces our new email classification approach, which exploits the similarity between email senders and recipients for their association into clusters, which are tagged by historical information. Our algorithms is designed to work together with any existing spam detection or filtering technique. Our goal is to provide a significant reduction of false positives (i.e., legitimate emails wrongly classified as spam), which can be as high as 15% in current filters [2].

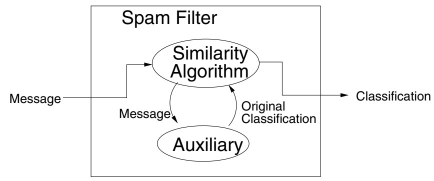


Figure 1: Architecture Proposed.

The architecture proposed in this paper is shown in Figure 1. A message arrives at the spam detection system and is directed to the structural similarity algorithm. This algorithm first sends the message to the auxiliary detection algorithm to retrieve a first classification of that message. Based on this classification, on the cluster formed by senders and recipients, and on previous historical information, our algorithm generates a new classification, which may or may not coincide with the original classification provided by the auxiliary. The idea is to use the classification provided by the auxiliary method to build an incremental historical knowledge base that becomes more representative as more messages are processed.

for all arriving message m **do**
  $mClass$ =classification of m by auxiliary detection method;
  sc =find cluster for $m.sender$;
  Update spam probability for sc using $mClass$;
  $P_s(m)$ =spam probability for sc;
  $P_r(m) = 0$;
  for all recipient $r \in m.recipients$ **do**
    rc =find cluster for r;
    Update spam probability for rc using $mClass$;
    $P_r(m) = P_r(m)+$spam probability for rc;
  end for
  $P_r(m) = P_r(m)/size(m.recipients)$
  $SP(m) =$ compute spam rank based on $P_s(m)$ and $P_r(m)$;
  if $SP(m) > \omega$ **then**
    classify m as spam;
  else if $SP(m) < 1 - \omega$ **then**
    classify m as legitimate;
  else
    classify m as $mClass$;
  end if
end for

Algorithm 1: New Algorithm for Email Classification

A description of the cluster-based algorithm is shown in Algorithm 1. This algorithm maintains sets of sender and recipient clusters, assembled from structural similarity, as defined in Equation (4). A sender/recipient of an incoming email is added to the sender/recipient cluster that is most similar to it, provided that their similarity exceeds a given threshold τ. Thus, τ defines the minimum similarity a sender/recipient must have with a cluster to be assigned to it. Varying τ allows us to create more or less tightly knit clusters. If no similar cluster can be found, a new single-user cluster is created.

The sets of sender and recipient clusters are updated at each new email arrival. Recall that to determine the cluster of a previous classified user we first remove the user from its current cluster and then assess its similarity to each existing cluster. Thus, single-user clusters tend to be reduced as more emails are processed, except possibly for users that appear only very sporadically.

A probability of sending/receiving spam messages is assigned to each sender/recipient cluster. We refer to this measure as the *cluster spam probability*. We calculate the spam probability of a sender/recipient cluster as the average spam probability of its elements, which, in turn, is estimated from the frequency of spams sent/received by each of them in the past. Therefore, our scheme uses the result of the email classification performed by the auxiliary algorithm on each arriving email m ($mClass$ in Algorithm 1) to continuously update cluster spam probabilities.

Let us define the probability of a message m being sent by a spammer, $P_s(m)$, as the probability of its sender's cluster send a spam. Similarly, let the probability of an email m being addressed to users that receive spam, $P_r(m)$, as the average spam probability of all of its recipients' clusters. Our algorithm uses $P_s(m)$ and $P_r(m)$ to compute a number that expresses the chance of email m being spam. We call this number the *spam rank* of email m, denoted by $SR(m)$. The idea is that emails with large values of $P_s(m)$ and $P_r(m)$ should have large spam ranks and thus should be classified as spam messages. Similarly, emails with small values of $P_s(m)$ and $P_r(m)$ should receive low spam rank and be classified as legitimate email.

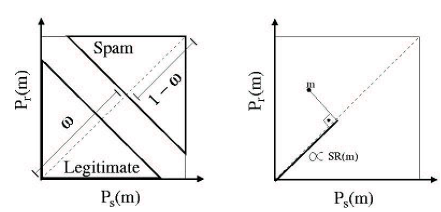


Figure 2: Spam Rank Computation and Email Classification for the Cluster-based Algorithm.

Figure 2 shows a graphical representation of the computation of the spam rank for a message. We first normalize the probabilities $P_s(m)$ and $P_r(m)$ by a factor of $\sqrt{2}$, so that the diagonal of the square region defined in the bi-dimensional space is equal to 1 (see Figure 2-left). Each email m is represented as a point in this square. The spam rank of m, $SR(m)$, is then defined as the length of the segment starting at the origin (0,0) and ending at the projection of m on the diagonal of the square (see Figure 2-right). With these definitions the spam rank varies between 0 and 1.

The spam rank $SR(m)$ is then used to classify m as follows: if it is greater than a given threshold ω, e.g. $\omega \geq 0.5$, the email is classified as spam; if it is smaller than $1 - \omega$, it is classified as legitimate email. Otherwise, we can not precisely classify the message, and we rely on the initial classification provided by the auxiliary algorithm. The parameter ω can be tuned to determine the precision of our classification. Graphically, emails are classified according to the marked regions shown in Figure 2-left. The two identical triangles represent the regions where our algorithm is able to classify emails as either spam (upper right) or legitimate email (lower left).

4 Experimental Results

In this section we describe our experimental results. We first present the most relevant details of our workload, followed by the quantitative results of our approach.

4.1 Workload

Our email workload consists of anonymized and sanitized SMTP logs of incoming emails to a large university in Brazil, with around 22,000 students. The server handles all emails coming from domains outside the university, sent to students, faculty and staff with email addresses under the university's domain name [1].

The central email server runs Exim email software [10], the AMaViS virus scanner [1] and the Trendmicro Vscan anti-virus tool [17]. A set of pre-acceptance spam filters (e.g. black lists, DNS reversal) blocks about 50% of the total traffic received by the server.

The messages not rejected by the pre-acceptance tests are directed to Spam-Assassin [16]. Spam-Assassin is a popular spam filtering software that detects spam messages based on a changing set of user-defined rules. These rules assign scores to each email received, based on the presence in the subject or in the email body of one or more pre-categorized keywords. Spam-Assassin also uses other rules based on message size and encoding. Highly ranked messages according to these criteria are flagged as spam.

We analyze a log collected from 01/02/2004 to 01/10/2004. Our logs store the header of each email (i.e. containing sender, recipients, size , date, etc.) that passes the pre-acceptance filters, along with the results of the tests performed by Spam-Assassin and the virus scanners. We also have the full body of the messages that were classified as spam by Spam-Assassin. Table 1 summarizes our workload.

Measure	Non-Spam	Spam	Aggregate
# of emails	168,352	153,494	321,846
Size of emails	7.5 GB	0.8 GB	8.3 GB
# of distinct senders	12,738	15,325	22,809
# of distinct recipients	23,849	25,383	34,065

Table 1: Summary of the Workload

By visually inspecting the list of sender *user names* [2] in the spam component of our workload, we found that a large number of them corresponded to a random sequence of characters, suggesting that spammers tend to change user names as an evasion technique. Therefore, for the experiments presented below we identified the sender of a message by his/her domain [3] while recipients were identified by their full address.

4.2 Classification Results

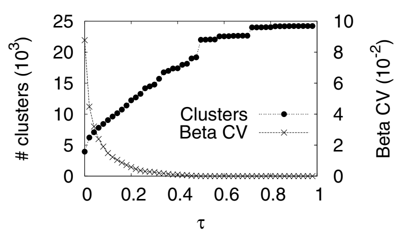


Figure 3: Number of Email User Clusters and Beta CV vs. τ.

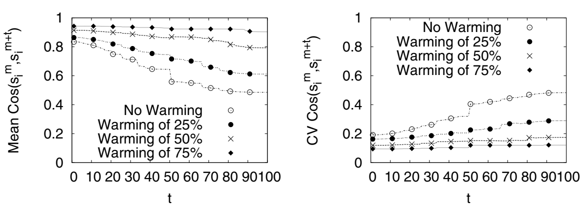
The results shown in this section were obtained through the simulation of the algorithm proposed in this paper over the set of messages in our logs. The implementation of the simulator makes use of an inverted list [20] approach for storing information about senders, recipients and clusters that is effective both in terms of memory and processing time. The classification rate of the simulations were both higher than the peak rate observed over the workload collection time [12].

The number and quality of the clusters generated through our similarity measure are the direct result of the chosen value for the threshold τ (see Section 3). In order to determine the best parameter value the simulation was executed several times for varying τ.

Figure 3 shows how the beta CV (Coefficient of Variation) for the clusters and the number of clusters vs. τ. Beta CV denotes the intra CV/inter CV for the clusters. Whereas the intra CV measures the coefficient of variation for the similarities intra-cluster, the inter CV measure the similarities between different clusters. Thus, beta CV is a measure of the quality of the clusters generated. The more stable the beta CV the better quality in terms of the grouping obtained [13]. There is one clear point of stability in the curve at $\tau = 0.5$ (Figure 3(a)).

Moreover, the number of clusters generated also stabilize at $\tau = 0.5$ (Figure 3(b)). This is the value we adopt for the remaining of the paper. Although other values of τ, above 0.5 would also be appropriate, the value of $\tau = 0.5$ results in a large number of non unitary clusters, allowing us to evaluate the benefits of the clustering of senders and recipients.

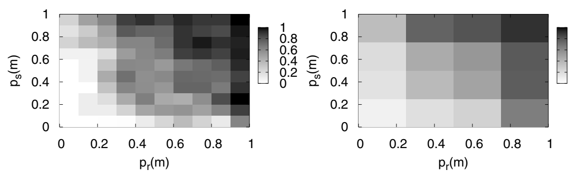
Our approach is motivated by two hypothesis. First, contact lists of email users provide an effective means for identifying them. Second, messages can be more accurately classified as spam or not based on the probabilities of sending/receiving spams of the cluster that their sender/recipients belong to.



(a) Mean Cosine (b) CV of Cosine

Figure 4: Spam Senders Identification Stabilization

In order to show that contact lists provide an effective user identification, we analyze how sender/recipient vectorial representations change over time, as new messages arrive in the system. In this analysis, we consider a warm-up period containing a certain fraction of the messages, during which sender/recipients are updated. We define $\vec{s_i^m}$ as the vectorial representation of sender i at a point in time when it had sent $m\%$ of its own messages (m is larger than the warm-up period). We use the similarity between the representations of sender i in two points in time, spaced by a certain fraction t of messages sent, as a measure of how stable the sender identification is over "period" t. We then analyze how this similarity, given by $cos(\vec{s_i^m}, \vec{s_i^{m+t}})$ evolves as the *step* t increases. Figure 4(a) shows average similarity measures for the senders in the spam traffic, varying the step from 1% to 100%, for different warm-up periods. Figure 4(b) shows the corresponding measures of coefficient of variation (CV). Note that, as expected, when there is no warm-up period ("No Warming"), fluctuations in the early messages dominate and stabilization is not reached by the end of our workload. In other words, a larger set of messages would be required for stabilization to be reached. As the warm-up period increases, stabilization is reached with a smaller number of messages. In particular, when we consider only the last 25% of the messages for each sender ("Warming of 75%"), sender representation remains, on average, very stable with CV approaching zero. Similar patterns were observed for legitimate e-mail senders as well as legitimate and spam recipients.

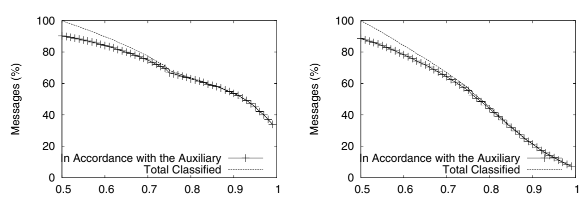


(a) Bin size = 0.10 (b) Bin size = 0.25

Figure 5: Number of Spam Messages by Varying Message Spam Probabilities for Different Bin Sizes.

Next, we investigate whether the second hypothesis hold. We plot, in figure 5, the fraction of spam messages in our workload for different values of $P_s(m)$ and $P_r(m)$ grouped based on a discretization of the full space represented in the plot. This space is subdivided into smaller squares of the same size called bins, the darker the gray scale the greater the number of spams in each bin. Clearly, spam and legitimate messages are located on the top-right and bottom-left regions of the spectrum as we have hypothesized in Section 3. There is, however, an intermediate region in the middle where we cannot satisfactorily determine the classification. This is why it becomes necessary to vary ω. One should adjust ω based on the level of confidence it has on the auxiliary algorithm.

Figure 5 shows that messages addressed to recipients that have high $P_r(m)$ tend to be spam more frequently than messages with the same value of $P_s(m)$. Analogously, messages with low $P_s(m)$ have higher probability of being legitimate messages.



(a) Legitimate (b) Spam

Figure 6: Messages Classified in Accordance With to the Auxiliary Algorithm and the Total Number of Messages Classified by Varying ω

Because our algorithm makes use of an auxiliary spam detection algorithm - e.g. SpamAssassin. Therefore, we need to evaluate how frequently we maintain the same classification as such an algorithm. Figure 6 shows the the percentage of messages that received the same classification and the total number of classified messages in our simulation by varying ω, considering only messages classified by the auxiliary as legitimate (Figure 6(a)) and spam (Figure 6(b)). The difference between these curves is the set of messages that were classified differently from the original classification.

Figures 6 also shows that, considering the sets of messages originally classified as legitimate and as spam, our algorithm is capable of classifying a larger number of messages from the former than from the latter. Moreover, we are slightly more conservative in the classification of legitimate emails than spams. We conjecture that both phenomena stem from the fact that the rules used by Spam Assassin tend to favor the detection of legitimate messages.

In another experiment, we simulated a different algorithm that also makes use of historical information provided by an auxiliary spam detector described in [19]. The main differences are that it uses historical information of each sender separately and it does not use recipients information. We built a simulator for this algorithm and executed it against our data set. The results show that it was able to classify 85.11% of the messages in accordance with the auxiliary algorithm, while our approach classify more than 95% with $\omega = 0.85$.

We believe that the differences between the original classification and the classification proposed for high ω values generally are due to misclassifications by the auxiliary algorithm. In our data set we have access to the full body of the messages that were originally classified as spam. We were able to evaluate a fraction of the total amount of false positives (messages that the auxiliary algorithm classify as spam and our algorithm classify as legitimate) that were generated by the auxiliary algorithm. This is important since the cost of false positives is usually believed higher than the cost of false negatives [7].

Algorithm	**% of Misclassifications**
Auxiliary	60.33%
Our approach	39.67%

Table 2: Possible False Positives Generated by the Approaches Studied.

Each of the possible messages classified by the auxiliary as spam and by our algorithm as legitimate was manually evaluated by three people, in order to determine whether such a message was indeed spam. Table 2 summarizes the results for $\omega = 0.85$, 879 messages (0.27% of the total messages) were manually analyzed. Our algorithm was correct in more 60% of the cases.

Due to the cost of manually classifying messages we can not afford to classify all of the messages categorized as spam by the auxiliary algorithm. However, we evaluate a randomly chosen fraction of the messages classified as spam by the auxiliary and by our algorithm, which represents the total data with a confidence interval of 99% [18]. With $\omega = 0.85$, we found that 15% of the total messages are in this group and we analyzed manually a sample of 3.50% (1,708 emails) of them. We found that 99.9% of the analyzed messages were correctly classified, showing the high precision of our classification.

Moreover, only 0.11% of the total of messages classified as legitimate by the auxiliary were found to be spam by our approach. Consequently, the total number of messages correctly moved from spam class to legitimate class is 47% greater than the number of messages moved from legitimate class to spam class by our algorithm. Moreover, we emphasize that we can not determine the quality of the classification for the messages classified as legitimate by the auxiliary algorithm since we do not have access to the full body of those messages.

5 Related Work

Several previous studies have focused on reducing the impact of spam email traffic. The approaches to reduce spam can be categorized into pre-acceptance and post-acceptance methods, based on whether they detect spam before or after accepting messages. Examples of pre-acceptance methods are server authentication [8, 4] and accountability [6]. Post-acceptance methods are mostly based on information available in the body of the messages and include Bayesian filters [15] and collaborative filtering [22].

Recent papers have focused on spam combat techniques based on characteristics of graph models of email traffic [5, 9]. In [5] a graph is created to represent the email traffic captured in the mailbox of individual users. The clustering coefficient of each of these components is used to classify messages as spam or legitimate. The results show that 53% of the messages were precisely classified using the proposed approach. In [9] the authors propose to detect machines that behave as spam senders by analyzing a border flow graph of sender and recipient machines. In contrast to these studies, we propose to use a structural similarity between email senders and recipients to group them into clusters and use the cluster historical information to improve spam detection. Moreover, unlike [5], our approach runs on the ISP level.

None of the existing spam filtering mechanisms are infallible [19, 7]. Their main handicap are false positives and wrong mail classification. In addition, filters must be continuously updated to capture the multitude of mechanism constantly introduced by spammers to avoid filtering actions. The algorithm presented in this paper aims at improving the effectiveness of spam filtering mechanisms, by reducing false positives and by providing information to tune their collection of rules.

6 Conclusions and Future Work

In this paper we proposed a new algorithm to improve spam detection based on the structural similarity between contact lists of email users. The idea is that contact lists, integrated over a suitable amount of time, are much more stable identifiers of email users than user names, domains or message contents, which can all be made to vary quickly and widely. The major drawback of our approach is that our algorithm can only group users based on their structural similarity, but has no way of determining by itself if such vector clusters correspond to spam or legitimate email. Thus it must work in tandem with an original classifier. Given this information we have shown that we can successfully separate spam and legitimate email users and that this structural inference can improve the quality of other spam detection algorithms.

Specifically we have implemented a simulator based on data collected from the main SMTP server for a major university in Brazil that uses SpamAssassin. We have shown that our algorithm can be tuned to produce classifications similar to those of the original classifier algorithm and that, for a certain set of parameters, is was capable of correcting false positives.

As future work, we intend to: (i) explore aging mechanisms to update the vectorial identification of senders and recipients over time, and (ii) study the robustness of our approach against different auxiliary classifiers.

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Notes

[1] Only the emails addressed to two out of over 100 university subdomains (i.e., departments, research labs, research groups) do not pass through the central server.

[2] The part before @ in email addresses.

[3] The part after @ of an email address