Improving Spam Detection Based on Structural Similarity

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Abstract

We propose a new detection algorithm that uses structural relationships between senders and recipients of email as the basis for the identification of spam messages. Users and receivers are represented as vectors in their reciprocal spaces. A measure of similarity between vectors is constructed and used to group users into clusters. Knowledge of their classification as past senders/receivers of spam or legitimate mail, coming from an auxiliary detection algorithm, is then used to label these clusters probabilistically. This knowledge comes from an auxiliary algorithm. The measure of similarity between the sender and receiver sets of a new message to the center vector of clusters is then used to assess the possibility of that message being legitimate or spam. We show that the proposed algorithm is able to correct part of the false positives (legitimate messages classified as spam) using a testbed of one week smtp log.

1 Introduction

The relentless rise in spam email traffic, now accounting for about 83% of all incoming messages, up from 24% in January 2003 [13], is becoming one of the greatest threats to the use of email as a form of communication.

The greatest problem in detecting spam stems from active adversarial efforts to thwart classification. Spam senders use a multitude of techniques based on knowledge of current detection algorithms, to evade detection. These techniques range from changes in the way text is written - so that it can not be directly analyzed computationally, but can be understood by humans naturally - to frequent changes in other elements, such as user names, domains, subjects, etc. Therefore, good choices for spam identifiers are becoming increasingly more difficult.

In the light of this enormous variability the question then is: what are the identifiers of spam that are most costly to change, from the point of view of the sender? The limitations of attempts to recognize spam by analyzing content are clear [6]. Content-based techniques[16, 21, 17] 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 spammers still need to reach recipients, even if under forged identifiers, 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 target a given recipient, i.e. the contacts of a user. The contact lists, or subsets thereof, can then be thought of as a 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 an algorithm for spam detection that uses structural relationships between senders and recipients as the basis for the identification of spam messages. The algorithm must work in conjunction with
another spam classifier, 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 (hereafter called: auxiliary algorithm). The key idea is that the lists spammers and legitimate users send messages to, as well as the lists from which they receive messages from can be used as the identifiers of classes of email traffic [19, 10]. We will show that the final result of the application of our structural algorithm over the determinations of the initial classifier leads to the correction of a number of misclassifications as false positives.

This paper is organized as follows: Section 2 presents the methodology used to handle email data. Our structural algorithm is described in Section 3. We present the characteristics of our example workload in section 4, as well as the classification results obtained with our algorithm over this 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 that exist in groups of senders and recipients as well as in the relationship established through the emails exchanged between them. This section introduces our modeling of individual email users and a metric to express the similarity existent among different users. It then extends the modeling to account for clusters of users who have great similarity.

Our basic assumption is that, in both legitimate email and spam traffics, users have a defined list of peers they often have contact with (i.e., they send/receive an email to/from). In legitimate email traffic, contact lists are consequence of social relationships on which users’ communications are based. In spam traffic, on the other hand, the lists used by spammers to distribute their solicitations are created for business interest and, generally, do not reflect any form of social interaction. A user’s contact list certainly may change over time. However, we expect it to be much less variable than other characteristics commonly used for spam detection, such as sender user-name, presence of certain keywords in the email content and encoding rules. In other words, we expect contact lists to be more effective in identifying spams and, thus, we use them as the basis for developing our algorithm.

We start by representing an email user as a vector in a multi-dimensional conceptual space created with all possible contacts. We represent email senders and recipients separately. We then use vectorial operations to express the similarity among multiple senders (recipients), and use this metric for clustering them. 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, etc).

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

\[
\hat{s}_i[n] = \begin{cases} 1, & \text{if } s_i \rightarrow r_n \\ 0, & \text{otherwise} \end{cases},
\]

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 representation for the recipient \( r_i \), where \( N_s \) is the number of distinct senders being considered. The \( n \)-th dimension of this vector is 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 vector representation (\( \hat{s}_i \) and \( \hat{s}_j \)). The similarity is computed as follows:

\[
sim(s_i, s_j) = \frac{\hat{s}_i \circ \hat{s}_j}{|\hat{s}_i||\hat{s}_j|} = \cos(\hat{s}_i, \hat{s}_j),
\]

where \( \hat{s}_i \circ \hat{s}_j \) is the internal product of the vectors and \( |\hat{s}_i| \) is the norm of \( \hat{s}_i \). Note that this metric varies from 0, when senders do not share any recipient in their contact lists, to 1, when senders have identical contact lists and thus have the same representation. The similarity between two recipients is defined similarly.

We note that our similarity metric has different interpretations in legitimate and spam traffics. In legitimate email traffic, it represents social interaction with the same group of people, whereas in the spam traffic, a great similarity 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 users (senders or recipients) who have great similarity. A sender cluster $s_{ci}$, represented by vector $\vec{s}_{ci}$, is computed as the vectorial sum of its elements, that is:

$$s_{ci} = \sum_{s \in sc_i} \vec{s}.$$  

(3)

The similarity between sender $s_i$ and an existing cluster $s_{cj}$ can then be directly assessed by extending Equation 2 as follows:

$$\text{sim}(s_{ci}, s_i) = \begin{cases} 
\cos(\vec{s}_{ci} - \vec{s}_{i}), & \text{if } s_i \in s_{ci} \\
\cos(\vec{s}_{ci}, \vec{s}_{i}), & \text{otherwise}
\end{cases}$$  

(4)

We note that a sender $s_i$ vectorial representation and thus the sender cluster to which it belongs (i.e., shares the greatest similarity) may change over time as new emails are considered. Therefore, in order to accurately estimate the similarity between a sender $s_i$ and a sender cluster $s_{ci}$ to which $s_i$ currently belongs, we first remove $s_i$ from $s_{ci}$, and then take the cosine between the two vectors ($\vec{s}_{ci} - \vec{s}_{i}$ and $\vec{s}_{i}$). This is performed so that the previous classification of a user does not influence its reclassification. Recipient clusters and the similarity between a recipient and a given recipient cluster are defined analogously.

### 3 A New Algorithm for Improving Spam Detection

This section introduces our new email classification algorithm which exploits the similarities between email senders and between email recipients for clustering and uses historical properties of clusters to improve spam detection accuracy. Our algorithm is designed to work together with any existing spamdetection and filtering technique that runs at the ISP level. 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].

A description of the proposed algorithm is shown in Algorithm 1. It runs on each arriving email $m$, taking as input the classification of $m$, $mClass$, as either spam or legitimate email, performed by the existing auxiliary spam detection method. Using the vectorial representation of email senders, recipients and clusters as well as the similarity metric defined in Section 2, it then determines a new classification for $m$, which may or not agree with $mClass$. The idea is that the classification by the auxiliary method is used to build an incremental historical knowledge base that gets more representative through time. Our algorithm benefits from that and outperforms the auxiliary one as shown in Section 4.

**Algorithm 1: New Algorithm for Email Classification**

```
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
    $P_s(m) = P_r(m)/\text{size}(m.recipients)$
    $SP(m) =$ 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
```

In order to improve the accuracy of email classification, our algorithm maintains sets of sender and recipient clusters, created based on the structural similarity of different users. A sender (recipient) of an incoming email is added to a sender (recipient) cluster that is most similar to it, as defined in Equation (4), provided that their similarity exceeds a given threshold $\tau$. Thus, $\tau$ defines the minimum similarity a sender (recipient) must have with a cluster to be assigned to it. Varying $\tau$ allows us to create more tightly or loosely knit clusters. If no cluster can be found, a new single-user cluster is created. In this case, the sender (recipient) is used as seed for populating the
new cluster.

The sets of recipient and sender clusters are updated at each new email arrival based on the email sender and list of recipients. Recall that to determine the cluster a previously observed, and thus clustered, user (sender or recipient) belongs to, we first remove the user from his current cluster and then assess its similarity to each existing cluster. Thus, single-user clusters tend to disappear as more emails are processed, except for users that appear only very sporadically.

A probability of sending (receiving) a spam is assigned to each sender (recipient) cluster. We refer to this measure as simply 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 based on the frequency of spams sent/received by each of them in the past. Therefore, our algorithm uses the result of the email classification performed by the auxiliary algorithm on each arriving email \( m \) (\( m_{\text{Class}} \) in Algorithm 1) to continuously update cluster spam probabilities.

Let us define the probability of an email \( m \) being sent by a spammer, \( P_s(m) \), as the spam probability of its sender’s cluster. 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 (see Algorithm 1). 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 receive low spam rank and be classified as legitimate email.

Figure 1 shows a graphical representation of the computation of an email spam rank. 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 1-left). Each email \( m \) can be 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 1-right). Note 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 \( \omega \), 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 email, and we rely on the initial classification provided by the auxiliary detection algorithm. The parameter \( \omega \) can be tuned to determine the precision that we expect from our classification. Graphically, emails are classified according to the marked regions shown in Figure 1-left. The two triangles, with identical size and height \( \omega \), 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 some important details of our workload, followed by the quantitative results of our approach, compared to others.

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 thousand 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.

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.
The central email server runs Exim email software [9], the Amavis virus scanner [1] and the Trendmicro Vscan anti-virus tool [18]. 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 [17]. 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 an eight-day log collected between 01/19/2004 to 01/26/2004. 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        | 191,417  | 173,584| 365,001   |
| Size of emails     | 11.3 GB  | 1.2 GB | 12.5 GB   |
| # of distinct senders | 12,338   | 19,567 | 27,734    |
| # of distinct recipients | 22,762 | 27,926 | 38,875    |

Table 1: Summary of the Workload

By visually inspecting the list of sender user names in the spam component of our workload, we found that a large number of them corresponded to a seemingly 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 while recipients were identified by their full address, including both domain and user name.

4.2 Classification Results

The results shown in this section were obtained through the simulation of the algorithm proposed here over the set of messages in our logs. The implementation of the simulator made use of an inverted lists [20] approach for storing information about senders, recipients and clusters that is effective both in terms of memory and processing time. Our simulations were executed on a commodity workstation (Intel Pentium® 4 - 2.80GHz - with 500MBytes) and the simulator was able to classify 20 messages per second. This is far faster than the average rate with which messages usually arrive and than the peak rate observed over the workload collection time [11].

![Figure 2](image-url)  
Figure 2: Number of Email User Clusters and Beta CV vs. \( \tau \).

![Figure 3](image-url)  
Figure 3: Number of Spam Messages by Varying Message Spam Probabilities for Different Bin Sizes.

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

Figure 2 shows how the number of clusters and beta
CV\(^3\) vary with \(\tau\). There is one clear point of stabilization of the curve (i.e. a plateau) at \(\tau = 0.5\) and that is the value we adopt for the remaining of the paper. Although other stabilization points occur for values of \(\tau\) above 0.5, the lowest of such values seems to be the most appropriate for our experiments. The reason for that is that this value of \(\tau\) is the one that generates the smaller number of clusters, i.e. cluster with more elements, and that allows us to evaluate better the beneficial effects that clustering senders and recipients may have. Moreover, while analyzing the beta CV we are able to see that the quality of the clustering for all values \(\tau > 0.4\) is approximately the same.

One of the hypothesis of our algorithm is that we can group spam messages in terms of the probabilities \(P_s(m)\) and \(P_r(m)\). Figure 3 shows the fraction of spam messages that exist for different values of \(P_s(m)\) and \(P_r(m)\) grouped based on a discretization of the full space represented in the plot. The full space is subdivided into smaller squares of the same size called bins. Clearly, spam/legitimate messages are indeed located in the regions (top and bottom respectively) as we have hypothesized in Section 3. There is however a region in the middle where we can not determine the classification for the messages based on the computed probabilities. This is why it becomes necessary to vary \(\omega\). One should adjust \(\omega\) based on the level of confidence he/she has on the auxiliary algorithm.

Figure 3 shows that differentiation between senders and recipients for detecting spam can be more effective than the simple choice we use in this paper. 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. Ways of using this information in our algorithm are an ongoing research effort that we intend to pursue in future extensions.

Our algorithm makes use of an auxiliary spam detection algorithm - such as SpamAssassin. Therefore, we need to evaluate how frequently we maintain the same classification as such an algorithm. Figure 4 shows the percentage of messages that received the same classification and the total number of classified messages in our simulation by varying \(\omega\). The difference between these curves is the set of messages that were classified differently from the original classification provided. There is a clear tradeoff between the total number of messages that are classifiable and the accordance with the previous classification provided by the original classifier algorithm.

In another experiment, we simulated a different algorithm that also makes use of history information provided by an auxiliary spam detector described in [19]. This approach tries to classify messages based on the historical properties of their senders. 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. Its important to note that, on the other hand, our algorithm can be tuned by the proper set of threshold \(\omega\). The higher the parameter \(\omega\) the more in accordance with the auxiliary classification the classification of our algorithm is.

We believe that the differences between the original classification and the classification proposed for high \(\omega\) 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. Therefore, we can evaluate a fraction of the total amount of false positives (messages that the auxiliary algorithm classify as spam and our algorithm classify as legitimate message) that were generated by the auxiliary algorithm. This is important since there is a common belief that the cost of false positives is higher than the cost of false negatives [6].

Each of the possible false positives were manually eval-
uated by three people so as to determine whether such a message was indeed spam. Table 2 summarizes the results for $\omega = 0.85$, 879 messages were manually analyzed (0.24% of the total of messages). Our algorithm outperforms the original classification since it generates less false positives. We emphasize that we can not similarly determine the quality of classification for the messages classified as legitimate by the auxiliary algorithm since we do not have access to the full body of those messages. Due to the cost of manually classifying messages we can not afford to classify all of the messages classified as spam by the auxiliary algorithm.

| Algorithm          | % of Missclassifications |
|--------------------|--------------------------|
| Original Classification | 60.33%                  |
| Our approach       | 39.67%                   |

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

5 Related Work

Previous work have focused on reducing the impact of spam. The approaches to reduce spam can be categorized into pre-acceptance and post-acceptance methods, based on whether they detect and block spam before or after accepting messages. Examples of pre-acceptance methods are black lists [14], gray lists [12], server authentication [7, 3] and accountability [5]. Post-acceptance methods are mostly based on information available in the body of the messages and include Bayesian filters [16], collaborative filtering [21].

Recent papers have focused on spam combat techniques based on characteristics of graph models of email traffic [4, 8]. The techniques used try to model email traffic as a graph and detect spam and spam attacks respectively in terms of graph properties. In [4] a graph is created representing the email traffic captured in the mailbox of individual users. The subsequent analysis is based on the fact that such a network possesses several disconnected components. The clustering coefficient of each of these components is then used to characterize messages as spam or legitimate. Their results show that 53% of the messages were precisely classified using the proposed approach. In [8] the authors used the approach of detecting machines that behave as spam senders by analyzing a border flow graph of sender and recipient machines. In[19], the authors propose a new scheme for handling spam. It is a post-acceptance mechanism that processes mail suspected of being spam at reduced priority, when compared to the priority assigned to messages classified as legitimate. The proposed mechanism[19] works in conjunction with some sort of mail filter that provides past history of mails received by a server.

None of the existing spam filtering mechanisms are infallible[19, 6]. Their main problems are false positive and wrong mail classification. In addition to those problems, 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 that help those mechanism to tune their collection of rules.

6 Conclusions and Future Work

In this paper we proposed a new spam detection algorithm 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 id 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. Because of this feature it must work in tandem with an original classifier. Given this information we have shown that we can successfully group spam and legitimate email users separately 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 generated by SpamAssassin in our workload.
There are several improvements and developments that were not explored here, but promise to reinforce the strength of our approach. We intend to explore these in future work. We observe that structural similarity gives us a basis for time correlation of similar addresses, and as such to follow the time evolution of spam sender techniques, in ways that suitably factor out the enormous variability of their apparent identifiers. Finally we note that the probabilistic basis of our approach lends itself naturally to the evolution of users’ classifications (say through Bayesian inference), both through collaborative filtering using user feedback and from information derived from other algorithmic classifiers.

References

[1] Amavis. http://www.amavis.org, 2004.
[2] ATKINS, S. Size and cost of the problem. In 56th IETF Meeting (March 2003).
[3] BAKER, H. P. Authentication approaches. In 56th IETF Meeting (March 2003).
[4] BOYKIN, P. O., AND ROYCHOUDHURY, V. Personal email networks: An effective anti-spam tool. http://www.arxiv.org/abs/cond-mat/0402143, February 2004.
[5] BRANDMO, H. P. Solving spam by establishing a platform for sender accountability. In 56th IETF Meeting (March 2003).
[6] CERF, V. G. Spam, spam, and spit. Commun. ACM 48, 4 (2005), 39–43.
[7] CRANOR, L. F., AND LAMACCHIA, B. A. Spam! In Communications of the ACM (1998).
[8] DESIKAN, P., AND SRIVASTAVA, J. Analyzing network traffic to detect e-mail spamming machines. Tech. Rep. 180, Army High Performance Computing Research Center TECHNICAL REPORT, 2004.
[9] Exim internet mailer home page. http://www.exim.org, 2004.
[10] GOMES, L. H., ALMEIDA, R. B., BETTENCOURT, L. M. A., ALMEIDA, V. A. F., AND ALMEIDA, J. M. Comparative graph theoretical characterization of networks of spam and regular email. http://arxiv.org/abs/cond-mat/0503725, March 2005.
[11] GOMES, L. H., CAZITA, C., ALMEIDA, J., ALMEIDA, V. A. F., AND JR., W. M. Characterizing a spam traffic. In Proc. of the 4th ACM SIGCOMM conference on Internet measurement (2004).
[12] HARRIS, E. The next step in the spam control war: Greylisting. http://projects.puremagic.com/greylisting/, April 2004.
[13] LABS, M. Message labs home page. http://www.messagelabs.co.uk/, 2005.
[14] Maps - mail abuse prevention system home page. http://mail-abuse.org/rbl/getoff.html, 2004.
[15] MENASCÉ, D., AND ALMEIDA, V. Capacity Planning for Web Services: metrics, models and methods. Prentice Hall Inc., USA, September 2001.
[16] SAHAMI, M., DUMAIS, S., HECKERMAN, D., AND HORVITZ, E. A bayesian approach to filtering junk E-mail. In Learning for Text Categorization: Papers from the 1998 Workshop (Madison, Wisconsin, USA, 1998), AAAI Technical Report WS-98-05.
[17] Spamassassin. http://www.spamassassin.org, 2004.
[18] Trend micro home page. http://www.trendmicro.com, 2004.
[19] TWNING, R. D., WILLIANSON, M. M., MOWBRAY, M., AND RAHMOUNI, M. Email prioritization: Reducing delays on legitimate mail caused by junk mail. In Proc. Usenix Annual Technical Conference (Boston, MA, June 2004).
[20] WITTEN, I. H., BELL, T. C., AND MOFFAT, A. Managing Gigabytes: Compressing and Indexing Documents and Images. John Wiley & Sons, Inc., New York, NY, USA, 1994.
[21] ZHOU, F., ZHUANG, L., ZHAO, B., HUANG, L., JOSEPH, A., AND KUBIATOWICZ, J. Approximate object location and spam filtering on peer-to-peer systems. In *Proc. of Middleware* (June 2003).