“In vivo” spam filtering:
A challenge problem for data mining

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ABSTRACT
Spam, also known as Unsolicited Commercial Email (UCE), is the bane of email communication. Many data mining researchers have addressed the problem of detecting spam, generally by treating it as a static text classification problem. True in vivo spam filtering has characteristics that make it a rich and challenging domain for data mining. Indeed, real-world datasets with these characteristics are typically difficult to acquire and to share. This paper demonstrates some of these characteristics and argues that researchers should pursue in vivo spam filtering as an accessible domain for investigating them.

General Terms
spam, text classification, challenge problems, class skew, imbalanced data, cost-sensitive learning, data streams, concept drift

1. INTRODUCTION
Spam, also known as Unsolicited Commercial Email (UCE) and Unsolicited Bulk Email (UBE), is commonplace everywhere in email communication. Spam is a costly problem and many experts agree it is only getting worse [24, 31, 53]. Because of the economics of spam and the difficulties inherent in stopping it, it is unlikely to go away soon.

Many data mining and machine learning researchers have worked on spam detection and filtering, commonly treating it as a basic text classification problem. The problem is popular enough that it has been the subject of a Data Mining Cup contest [10] as well as numerous class projects. Bayesian analysis has been very popular [20, 21, 16, 3], but researchers have also used SVMs [20], decision trees [1], memory and case-based reasoning [28, 5], rule learning [27], and even genetic programming [19]. But researchers who treat spam filtering as an isolated text classification task have only addressed a portion of the problem. This paper argues that real-world in vivo spam filtering is a rich and challenging problem for data mining. By “in vivo” we mean the problem as it is truly faced in an operating environment, that is, by an on-line filter on a mail account that receives realistic feeds of email over time, and serves a human user. In this context, spam filtering faces issues of skewed and changing class distributions; unequal and uncertain error costs; complex text patterns; a complex, disjunctive and drifting target concept; and challenges of intelligent, adaptive adversaries. Many real-world domains share these characteristics and would benefit indirectly by work on spam filtering.

Improving spam filtering is a worthy goal in itself, but this paper takes the (admittedly selfish) position that data mining researchers should study the problem for the benefit of data mining. It is unclear whether spam filtering efforts could genuinely benefit from data mining research. On the other hand, one of the persistent difficulties of research in many real-world domains is that of acquiring and sharing datasets. Most companies, for example, do not release customer transaction data; we are aware of no public domain datasets containing genuine fraudulent transactions for studying fraud detection. Even sharing such data between partner companies usually requires formal non-disclosure agreements. In other domains datasets may still have copyright or privacy issues. Few datasets involving concept drift or changing class distributions are publicly available. Without such datasets, the ability to replicate results and to compare algorithm performance is hindered and progress on these research topics will be impaired. Spam data are easily accessible and shareable, which makes spam filtering a good domain testbed for investigating many of the same issues. The remainder of the paper enumerates these research issues and describes how they are manifested in in vivo spam filtering. The final section of the paper discusses how researchers could begin exploring the domain.

2. CHALLENGES
2.1 Skewed and drifting class distributions
Like most text classification domains, spam presents the problem of a skewed class distribution, i.e., the proportion of spam to legitimate email is uneven. There are no generally agreed upon class priors for this problem. Gómez Hidalgo [13] points out that the proportion of spam messages reported in research datasets varies considerably, from 16.6% to 88.2%. This may be simply because the proportion varies considerably from one individual to another. The amount of spam received depends on the email address, the degree
of exposure, the amount of time the address has been public and the upstream filtering. The amount of legitimate email received similarly varies greatly from one individual to another.

Perhaps more importantly, spam varies over time as well. This was demonstrated dramatically in 2002 when a large number of open relays and open proxies were brought on-line in Asian countries, primarily Korea and China. Such a large new pool of unprotected machines provided great opportunities for spammers, and soon email servers throughout the world experienced a huge surge in the amount of spam they forwarded and received. The problem became so bad that for a brief time all email from certain Asian countries was blocked completely by some ISPs.

In spite of claims that spam is generally increasing, the volume varies considerably and non-monotonically on a daily or weekly scale. Calculating spam proportion even approximately is difficult. Although some public spam datasets are available (see Appendix A), we are aware of no personal email datasets arranged over time, so it is difficult to match the two to establish priors. Nevertheless, using

de several datasets we can make a case that spam priors change significantly over time.

Figure 1 shows a graph of spam volume received in 2002 by Paul Wouters of Xtended Internet. In 2002 the spam volume was $146 \pm 55$ messages per week, indicating a great deal of variation in spite of its upward trend. For most people, the volume of the legitimate email received varies as well. Figure 1 shows a graph of the number of legitimate messages saved by the author over the weeks in 2002. The volume is $12.3 \pm 6.4$ messages per week.

Figure 2 shows the volume of reports issued from SpamCop’s website. This graph also demonstrates some of spam’s episodic nature. SpamCop is a service used by many people to filter spam and to submit reports (complaints) to the originators of spam. Both the amount of spam submitted and the number of reports sent show clear episodic behavior. These graphs show time variation in both the volume of

http://spamarchive.xtdnet.nl/
http://www.spamcop.net/spamstats.shtml
spam and the volume of legitimate email received, something that researchers have not generally acknowledged. Since the two sources of email—senders of spam and senders of legitimate email—are independent parties with little in common, we can expect their variation to be statistically uncorrelated, and the class priors will vary over time. No fixed prior will be correct.

How much could we expect class priors to vary? If we assume that a user received the spam shown in figure 1a and the legitimate email shown in figure 1b, we can estimate the class prior $p(\text{spam})$ simply as the proportion of weekly messages that are spam. Figure 3 shows a graph of this value, which ranges between about .67 to .99.

A further demonstration of changing priors appears in Kristian Eide’s study of bayesian spam filters [12]. In evaluating these filters he measured the volume of spam and legitimate email he received over the course of one month. These volumes are graphed in figure 4a, and the computed daily spam prior is graphed in figure 4b. The prior ranges from .32 to .9, showing greater variation than in figure 3, though the skew is not as high.

Variation in class priors may be problematic for researchers because it makes solution superiority more difficult to establish. A classifier that performs better than another on a dataset with 80% spam may perform worse on one with 40% spam [20].

Should researchers be concerned about these varying class priors? This question is difficult to answer conclusively because it depends on classifier performance as well as error cost assumptions (discussed in section 2.2). But by employing the cost curve framework of Drummond and Holte [11], we can answer a related question, How much of cost space is influenced by this variation? This question can be answered by calculating the span of the Probability Cost Function (PCF), which is the $x$ axis of a cost curve. The PCF ranges from zero to one and is a function of the class prevalence and the ratio of misclassification error costs. In the case of spam:

$$\text{PCF}_{\text{spam}} = \frac{p(\text{spam}) \cdot \text{cost}(\text{FN})}{p(\text{spam}) \cdot \text{cost}(\text{FN}) + p(\text{legit}) \cdot \text{cost}(\text{FP})}$$

If we assume that the cost of a false positive (that is, of classifying a legitimate message as spam) is about ten times that of a false negative, this reduces to

$$\text{PCF}_{\text{spam}} = \frac{p(\text{spam})}{p(\text{spam}) + p(\text{legit}) \times 10}$$

Using the $p(\text{spam})$ range from figure 4b, the PCF range of interest for spam filtering is $0.04 \leq \text{PCF}_{\text{spam}} \leq 0.47$. Since the entire PCF range is $[0,1]$, this means nearly half of cost space is influenced by this variation in priors. Any classifier whose performance lies within this 44% could be a competitive solution. This is a wide range, and it is reasonable to expect classifier superiority to vary within it.

The purpose of this analysis is not to call into question the validity of prior work, but to point out that changing class distributions are a reality in this domain and their influence on solutions should be tested. Conversely, researchers investigating skewed and varying class distributions would do well to study the spam filtering problem.

Exactly how a researcher should best track and adjust class priors is an open question and will require research. Time series work in statistics should provide some strategies, for example, using an exponentially decayed average of recent priors. However researchers estimate priors, they should acknowledge that priors vary and static values are unrealistic.

### 2.2 Unequal and uncertain error costs

A further complication of in vivo filtering is the asymmetry of error costs. Viewing the filter as a spam classifier, a spam message is a positive instance and a legitimate message is a negative instance. Judging a legitimate email to be spam (a false positive error) is usually far worse than judging a spam email to be legitimate (a false negative error). A false negative simply causes slight irritation, i.e., the user sees an undesirable message. A false positive can be critical. If spam is deleted permanently from a mail server, a false positive can be very expensive since it means a (possibly important) message has been discarded without a trace. If spam is moved to a low-priority mail folder for later human scanning, or if the address is only used to receive low priority
email, false positives may be much more tolerable. In an essay on developing a bayesian spam filter, Paul Graham describes the different errors in an insightful comment:

> False positives seem to me a different kind of error from false negatives. Filtering rate is a measure of performance. False positives I consider more like bugs. I approach improving the filtering rate as optimization, and decreasing false positives as debugging.

Ken Schneider, CTO of the mail filtering company BrightMail, makes the same point more starkly. He argues that filtering even a small amount of legitimate email defeats the purpose of filtering because it forces the user to start reviewing the spam folder for missed messages. Even a single missed important message may cause a user to reconsider the value of spam filtering. This argues for assigning a very high cost to false positive errors.

Regardless of the exact values, these asymmetric error costs must be acknowledged and taken into account by any acceptable filtering solution. Judging a spam filtering system by accuracy (or, equivalently, error rate) is unrealistic and misleading. Some researchers have measured precision and recall without questioning whether metrics for information retrieval are appropriate for a filtering task.

Fortunately, most researchers have acknowledged these asymmetric costs, but methods for dealing with them have been ad hoc. The 2003 Data Mining Cup Competition required that learned classifiers have no more than a 1% false positive rate, but the organizers gave no justification for this cut-off. Graham simply double-counted the tokens of his legitimate email, essentially considering the cost of a false positive to be twice that of a false negative. Sahami et al. used a very high probability threshold of .999 for classifying a message as spam. Androutsopoulos et al. performed more careful experiments across cost ratios of 1, 10 and 100, exploring two orders of magnitude of cost ratios. These approaches suggest a deeper issue: true costs of filtering errors may simply be unknown to the data mining researcher, or may be known only approximately. Only the end user will know the consequences of filtering mistakes and the run-time filter should accommodate. Admittedly this requirement complicates research evaluation since the superiority of an approach may not extend throughout a cost range, and multiple experiments may have to be performed.

Such uncertainty is actually common in real-world domains, where experts may have difficulty stating the exact cost of an erroneous action, or the cost of the action may vary depending on external circumstances. This situation motivated development of a framework based on ROC analysis for evaluating and managing classifiers when error costs are uncertain. In the case of spam filtering, the uncertainty of error costs may not change temporally but they do vary between users. Gómez Hidalgo used this framework for developing and evaluating spam filtering solutions, and found it useful. Drummond and Holte have also developed a cost curve framework that extends ROC analysis and serves much the same purpose. Whatever technique is used for evaluating classifier performance, researchers should be prepared to demonstrate a solution’s performance over a range of costs.

### 2.3 Disjunctive and changing target concept

Section made the case that the amount of spam drifts over time, so class distributions vary. It is also true that the content of spam changes over time, so class-conditioned feature probabilities will change as well. Some spam topics are perpetual, such as advertisements for pornography sites, offers for mortgage re-financing, and moneymaking schemes. Other topics are bursty or occur in epidemics.

One notorious example of a spam ploy coming into vogue is the “Nigerian Money” scam, a get-rich-quick scam in which help was solicited to transfer money from a Nigerian bank account. The details varied, but the sender usually claimed to be responsible for a large bank account and requested assistance in “liberating” the funds from the Nigerian government. The sender was willing to pay generously for access to a foreign bank account into which the money would be transferred. This account was usually drained of funds once access was granted. Eventually the people responsible for the scam were arrested, and spam of that type declined quickly (unfortunately, variants continue to circulate as other people adopt the general idea). Prior to this scam, keywords such as nigeria and assistance were not strong predictors of spam.

A more dramatic episode occurred in April of 2003 when decks of playing cards depicting “Iraq’s Most Wanted” were made available for sale. These cards were advertised primarily via spam. The advertising campaign created such a spam blizzard that its story—and the campaign’s success—were written up in the New York Times. This campaign abated quickly and few of the terms uniquely associated with this episode retain much predictive power now.

The point for researchers is that spam content changes so the “spam” concept should drift inevitably. Some components (disjuncts) of the concept description should remain constant or change only slowly. Others will spike during epidemics, as specific scams or merchandising schemes come into vogue. Even perpetual topics do not exhibit constant term frequencies.

It is difficult to estimate how much we can expect “spam” as a concept to drift over time, in part because no metric of concept drift in spam has been adopted by the community. It is beyond the scope of this paper to present a rigorous investigation of concept drift in spam, but a simple technique can demonstrate significant word frequency variation.

Swan and Allan employed a χ² test to discover “bursty” topics in daily news stories. Their test was designed to determine whether the appearance of a term on a given day was statistically significant. This test can be applied to weekly groups of spam messages in Wouters’ archive, using the average weekly frequency of a term as its expected value. The results are shown in figure with selected terms listed on the left side and a column for every week (1–52) of 2002 extending to the right. The height of a bar at a term-week is proportional to the term’s frequency in that week. The special symbol “$\mathcal{D}$” denotes a term burst: it appears in a term’s row if that term appeared more than four times in the week and the $\chi^2$ test succeeded at $p < 0.01$.

Figure shows that spam has complex time-varying behav-
ior. Some terms recur intermittently, such as adult, click, free, hot and removed. Others are episodic, e.g., the terms common in a “Nigerian scam” burst in week 18 (nigeria, lagos, assistance, beneficiary) and terms in a “pornstar videos” burst in weeks 31–32 (orgy, awesome, pornstars, jenna, lauren, nicki). The term christmas bursts late in the year and presumably reappears every year around the same time. Spam behavior is not simply a matter of one concept drifting to another in succession, but instead is a superimposition of constant, periodic and episodic phenomena. Researchers in data mining have studied classification under concept drift but it remains an open problem. Work in Topic Detection and Tracking [1] is likely to be relevant to spam classification, though technically it addresses a different problem. No detailed study of real-world concept drift has yet been undertaken, and to the best of our knowledge there are no standard datasets for studying it. A longitudinal spam dataset would be an excellent testbed for investigating issues in concept drift and stream classification.

### 2.4 Intelligent adaptive adversaries

The spam stream changes over time as different products or scams, marketed by spam, come into vogue. There is a separate reason for concept drift: spammers are engaged in a perpetual “arms race” with email filters [7; 35]. Over time spammers have become increasingly sophisticated in their techniques for evading filtering [23]. In its early days, spam would have predictable subject lines like MAKE MONEY FAST! and Refinance your mortgage. Messages would be addressed to Undisclosed recipients or nobody. As basic header filtering became common in e-mail clients, these obvious text markers were simple to filter upon so spam could be discarded easily. As message body scanning became common, fragments such as viagra and click here

![Week of 2002]

| Term         | Week 1 | Week 10 | Week 20 | Week 30 | Week 40 | Week 50 |
|--------------|--------|---------|---------|---------|---------|---------|
| orgy         | ✔️     |         | ✔️      |         | ✔️      | ✔️      |
| accept       | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| adult        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| amateur      | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| application  | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| assistance   | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| awesome      | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| beneficiary  | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| billionaire  | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| cards        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| casino       | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| checks       | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| christmas    | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| click        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| debtfree     | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| deposit      | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| dirty        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| fortune      | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| free         | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| girls        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| horny        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| hot          | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| hottest      | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| insurance    | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| jenna        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| lagos        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| lauren       | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| loan         | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| merchant     | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| mortgage     | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| nicki        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| nigeria      | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| pornstars    | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| postmaster   | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| promotion    | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| removed      | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| viagra       | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| videos       | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| virus        | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |
| weight       | ✔️     | ✔️      | ✔️      | ✔️      | ✔️      | ✔️      |

Figure 5: Frequency and burstiness of spam terms.
could be checked for as well. To circumvent simple filtering, spammers began to employ content obscuring techniques such as inserting spurious punctuation, using bogus HTML tags and adding HTML comments in the middle of words. It is now common to see fragments such as these:

- v ia.g. ra
- 100%, Money Back Guarantee!
- Our pro<ur2ad9/>duict is doctor reco<br2z9

/mmchen<ur2ad9/>ded and made from 100%

/nauc<ur2ad9/>ral ingre<ur2ad9/>/dients.
- <c!---7udz15315pp6--->lic<--yajievn1xbecz2-->k



he<--ele0aj2pwwu--><e</a>
- Innocéasé tééstétérénné by 254%

When rendered, these are recognizable to most people but they foil simple word and phrase filtering. To counter this, some filters remove embedded punctuation and bogus HTML tags before scanning, and consider them to be additional evidence that the message is spam.

Spammers are also aware that filters use Bayesian word analysis and content hashing, so they often pepper their messages with common English words and nonsense words to foil these techniques [21]. Messages are designed so these words are discarded when the text is rendered, or are rendered unobtrusively. Graham-Cumming [17] maintains an extensive catalog of the techniques used by spammers to confuse filters.

Whatever new filtering capabilities arise, it is just a matter of time before spammers find ways to evade them. In machine learning terms, spammers have a strong interest in making the “spam” and “legitimate” classes indistinguishable. Because the discrimination ability of spam filters improves continually, the resulting concept drifts.

Because of this text distortion, in vivo spam filtering diverges significantly from most text classification and information retrieval problems, where authors are not deliberately trying to obfuscate content and defy indexing. Researchers should expect that they will have to develop techniques unknown in these related fields. Much of the effort of developing spam filters will probably shift from feature combining (i.e., experimenting with different induction algorithms) to feature generation (i.e., devising automatic feature generation methods that can adapt to new distortion patterns).

Such an arms race is not uncommon. Co-evolving abilities appear often when access to a desired resource is simultaneously sought and blocked by intelligent, adaptive parties. Fraud analysts observe criminals developing increasingly sophisticated techniques in response to security improvements [15]. With spam, the desired resource is the attention of email users, and spam may be seen as a way of illicitly gaining access to it. Another example of an arms race occurs in e-commerce. As pricing schemes have become more sophisticated, consumers have become more adept at gaming the systems. Sophisticated “shop bots” have been developed, and on-line merchants have had to develop ways to keep pricing information from them. Both sides continue to improve their techniques. Finally, the well-publicized conflict between the music swapping networks and the American music industry shows characteristics of an arms race, as both sides develop more sophisticated methods in their battle over access to copyrighted material [21].

Such co-adaptation of intelligent agents is foreign to most data mining researchers: the data are mined and the results are deployed, but the data environment is not considered to be an active entity that will react in turn. With the internet, much information is freely and automatically available by all parties, and interactivity is the rule. I propose that the future will bring more scenarios involving feedback and co-adaptation. Data miners may have to consider the effects of mining on their task environment, and perhaps incorporate such mechanisms into the data mining process. Possible strategies include concealing one’s deployed techniques from adversaries, incorporating deception into techniques, or simply speeding up the deployment cycle to adapt more quickly to adversaries’ moves. Spam filtering could be a useful domain in which to explore such strategies.

3. MEETING THE CHALLENGE

This paper has made the case that in vivo spam filtering can be a complex data mining problem with difficult challenging characteristics:

- Skewed and changing class distributions
- Unequal and uncertain error costs
- Complex text patterns requiring sophisticated parsing
- A disjunctive target concept comprising superimposed phenomena with complex temporal characteristics
- Intelligent, adaptive adversaries

Researchers wishing to explore these issues would do well to study in vivo spam filtering. Controlled laboratory datasets exhibiting these characteristics are often difficult to acquire and to share. Spam filtering, on the other hand, is an excellent domain for investigating these problems.

Researchers wishing to pursue this domain should begin collecting longitudinal data in a controlled manner. Spam is notoriously easy to attract. Several studies have measured the extent to which various activities attract spam [22, 23], and this information may be useful. It is easy to create ad hoc email addresses (for example, through Hotmail or Yahoo) and to advertise them in a controlled manner to attract spam. Such addresses are sometimes called “spam traps” and are used by email filtering companies such as BrightMail to obtain a continuous clean feed of spam for analysis.

A more difficult problem is that of obtaining shareable corpora of non-spam email, which often contain personal details that people want to keep private. Two general approaches have been taken:

1. Researchers who have contributed personal email have sought ways to anonymize it. The contributors of the UCI “spambase” dataset achieved this by reducing the original messages to word frequencies and performing feature selection upon the set. Unfortunately, this makes it difficult for other researchers to experiment with alternative feature selection or text processing operations on the data.
Androutsopoulos et al. [2] have developed a basic encoding technique for sharing data without compromising privacy. Their software and several of their datasets are available; see Appendix A.

2. Androutsopoulos et al. [3] have suggested using messages from websites and public mailing lists as proxies for personal email. Their “Ling-span” corpus uses messages from the moderated Linguist list. Other researchers have suggested that such messages may not be representative of the email most people receive. Whether this renders mailing list data ineffective for exploring in vivo spam filtering remains to be studied.

However researchers decide to generate such corpora, they should consider making their data publicly available. This article has outlined the challenges of in vivo spam filtering and explained how pursuing such challenges could help data mining. It is hoped that this article stimulates interest in the problem. The appendix and references should serve as useful resources for researchers wishing to pursue it.

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APPENDIX

A. SOURCES OF SPAM DATA

There are several sources of spam data on the internet, though researchers should be aware of their limitations.

1. Several static databases have been used by the machine learning community. The UCI database “spambase” [4] has a featurized version of spam and legitimate email. Androutsopoulos et al. [3] have made available several of their corpora containing both spam and personal email. All are available for download from http://www.iit.demokritos.gr/skel/i-config/. Note that messages in these databases are not reliably timestamped so they are not useful for measuring time-varying aspects of spam.

2. Paul Wouters, of Extended Internet, has an extensive archive of spam available at http://spamarchive.xtdnet.nl/. His archive covers several years. His messages from 2002 were used to produce figures 1a and 5.

3. Richard Jones of Annexia.Org has made a longitudinal spam archive available at ftp://ftp.ics.uci.edu/pub/machine-learning-databases/spambase. Although his messages are carefully timestamped, note his explanation about the large drop around mid-2002, attributed to deleting a number of old mail accounts. For this reason I avoided making inferences about spam volume from his dataset.

4. SpamArchive.org is a “community resource used for testing, developing, and benchmarking anti-spam tools. The goal of this project is to provide a large repository of spam that can be used by researchers and tool developers.” Current SpamArchive has over 200K spam messages and receives about 5000 messages per day.

5. Bruce Guenter has a longitudinal database of spam available at http://www.em.ca/~bruceg/spam/. See the caveat below about measuring spam volume.

Note that these datasets are archives of spam saved over time and were not designed to be controlled research datasets. It is important to understand the limitations of measuring spam volume from any of them. They are kept by owners of entire sites rather than individual accounts so the spam may be extracted from several mailboxes. The mailboxes may include admin and webmaster, which are believed to receive more spam than average. Some of these administrators even use “spam trap” addresses deliberately to attract spam. Finally, note that being active on Usenet or the web can often get a user added to spamming lists—as can making a spam archive available on the web. For all of these reasons, these spam archives may contain more spam than the average email user typically gets.

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