

# Metrics for Measuring ISP Badness: The Case of Spam (Short Paper)

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## Abstract

We consider the problem of ISP targeting for spam prevention through disconnection. Any such endeavor has to rely on adequate metrics that consider both the badness of an ISP as well as the risk of collateral damage. We propose a set of metrics that combines the two. Specifically, the metrics compare each ISP's "spamcount" with its "disconnectability". We offer a concrete methodological approach to compute these metrics, and then illustrate the methodology using datasets involving spam statistics and autonomous system relationships. This analysis represents the first step in a broader program to assess the viability of economic countermeasures to spam and other types of malicious activity on the Internet.

## 1 Introduction and Related Work

Recent studies have shown that a large percentage of all spam on the Internet is attributable to sources from a small percentage of the Internet's autonomous systems [3, 8, 24]. Thus in considering the spam-prevention problem, it makes sense to concentrate attention on those few systems who contribute to the problem the most. Evidence suggests that targeting an especially bad player can be effective. For example, the November 2008 takedown of McColo [6, 9] resulted in a significant decline in the global volume of spam (by estimates as much as 70%) [19].<sup>5</sup>

In this work, we address the targetability question by defining metrics to determine when an autonomous system is doing substantially more harm than good. These metrics can then be used not just for assessing the feasibility of targeting an ISP, but also for recognizing which ISP's may be susceptible to economic incentive structures designed to elicit implementation of outbound preventative mechanisms. The set of metrics we propose are based on ratios between "badness" measures which quantify the ill effects an autonomous system (AS) poses to the rest of the network, and "disconnectability" measures that quantify the collateral damage that would result from the AS's disconnection from the Internet graph.

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<sup>5</sup> There are also bad registrars but that is a different story [18].

## 1.1 Spam Measurement Studies and Mitigation

There is a diverse and growing literature on the measurement of spam and other network threats. Ramachandran and Feamster showed that network level properties can reveal decisive cues in the fight against spam [24]. Other contributions are the development of behavior-driven or signature-driven spam classification systems which are desirable given the transient nature of spam origins [12, 14, 25, 27, 33].

A number of studies have investigated the problem of botnet identification [11, 23, 34]. Ehrlich *et al.* proceed with a two-step methodology. First, they identify individual botnet nodes. Second, they continue their investigation to determine the command-and-control infrastructure of the botnet. In related projects, research groups have worked on building infrastructures to identify rogue networks [15, 28].

Finally, a growing number of research studies is concerned with the better understanding of spam economics, by studying large-scale spam campaigns [1, 4, 16], and by tracing click trajectories to better understand the spam value chain [20].

## 1.2 Economics of Service Provisioning and Security

Several reports have explored the economic incentives of Internet Service Providers to invest in security measures [3, 32]. A key observation is that ISPs respond differently to emerging threats leading to varying degrees of botnet infestations in their user population [3]. Some ISPs may act vigorously, while others appear to be slacking [5]. Finally, a residual group aims to derive a profit from providing a safe harbor for undesirable activities [8].

ISPs are in an excellent position to address security problems [2]. However, it is an open debate whether or to what degree liability can be assigned to them for insufficient or even detrimental behaviors [21].

But even from the perspective of well-motivated ISPs it is not obvious how to address security threats in a cost-efficient manner [26]. ISPs can incentivise users to higher security vigilance, but there are tradeoffs. Some incentive schemes target higher individual security effort levels [29], while others focus more on group-level security outcomes [13].

Another approach is to reduce the autonomy of individual users by installing security client software that monitors and controls network access. However, the majority of consumer-oriented ISPs shy away from direct technical intervention involving access to the users' home resources. Some argue this to be a government's role [7]. We are only aware of one US consumer ISP experimentally testing a similar approach [22]. However, several ISPs utilize redirection and quarantining techniques to encourage users to engage in clean-up efforts [17].

The rest of the paper is organized as follows. In Section 2, we define several metrics for use in ranking autonomous systems according to their miscreant behavior and discuss their key properties. In Section 3, we briefly describe our methodology for computing the proposed metrics on real data. Section 4 contains examples and illustrations pertaining to the ASes responsible for the most spam volume in our dataset. We discuss plans for future work and conclude in Section 5.

## 2 Proposed Metrics

In this section, we introduce metrics to formally quantify the *badness* and *disconnectability* of autonomous systems, along with the *cost-benefit tradeoff* that can be used as part of a formal basis for decisions involving AS targeting.

With respect to a given set of connectivity relations between autonomous systems, we define the following associated set of ASes. The *exclusive customer cone* of an autonomous system  $X$  is the set of autonomous systems that would become disconnected from the network if  $X$  were completely disconnected from the rest of the network. Note that every AS is a member of its own exclusive customer cone. The exclusive customer cone of  $X$  is a subset of the *customer cone* of  $X$ , which was defined by Dimitropoulos *et al.* as the set of customers of  $X$  together with those customers' customers, and so forth [10]. By way of contrast, the exclusive customer cone does not include those customers and subcustomers of  $X$  with a connection to at least one additional provider that can move traffic to the core of the network while avoiding  $X$ . The customer cone is a reasonable measure of the importance of  $X$ , but the exclusive customer cone has a more direct bearing on the question of whether to target  $X$ .

We next define a set of three metrics related to the exclusive customer cone. The *exclusive customer cone size* of  $X$  is the number of ASes in the exclusive customer cone of  $X$ . The *exclusive customer cone prefix size* of  $X$  is the number of distinct /24 prefixes assigned to ASes in the exclusive customer cone of  $X$ . The *exclusive customer cone address size* of  $X$  is the number of IP addresses assigned to ASes in the exclusive customer cone of  $X$ .

With respect to a given set of data attributing spam to IP addresses, we define the following two metrics. The *spamcount* of an autonomous system  $X$  is the number of spam messages attributable to IP addresses directly assigned to  $X$ . The *spamipcount* of  $X$  is the number of distinct IP addresses directly assigned to  $X$  that are responsible for sending at least one spam message. We can obviously extend these definitions to negative attributes other than spam. For example, we could analogously define the *badness* of  $X$  and the *ipbadness* of  $X$  relative to any data set that associates a measure of badness to certain IP addresses.

Lastly with respect to both a badness measure on IP addresses and a set of connectivity relations among autonomous systems, we define a set of ratio metrics comparing the two. For example, the *spamipcount to exclusive customer cone prefix size ratio* of an autonomous system  $X$  is the ratio of the spamipcount of  $X$  to the exclusive customer cone prefix size of  $X$ .

## 3 Methodology

In this section, we briefly describe a methodological approach to computing these metrics on real data.

The metrics require three types of data for autonomous systems: a notion of badness for each AS; a measure of size for each AS; and the AS customer/peer relationship structure. The current state of the art in relationship structure is publicly available via the Cooperative Association for Internet Data Analysis (CAIDA) [31]. CAIDA also publishes size measures for autonomous systems.

Measures of badness come in many forms, and good datasets are more difficult to obtain. We carried out an illustration of our methodology using a data source consisting of about 3.4 million spam email messages collected by Ramachandran and Feamster at Georgia Tech over a period of about 17 months starting in July 2008. The methodology of that data collection was previously used and is described in an earlier publication [24]. We processed these emails to obtain a best guess source IP for each email; and then used the bulk Whois query tools provided by Team Cymru [30] to associate IP addresses obtained from the spam dataset with their associated autonomous system numbers.

## 4 Examples and Observations

The purpose of this section is to exemplify our methodological approach through illustration.

### 4.1 Exclusive Customer Cone Properties

Figure 1 in the appendix offers visualizations of the exclusive customer cones for two of the five most spammy ASes in our dataset: 4134 and 4837. The edges reflect provider-to-customer relationships. The diameter of each node increases linearly with the node’s spamcount, and the color of the node moves from green to red as the spamcount to exclusive customer cone prefix size ratio increases.

### 4.2 Aggregated Spam Characteristics

Figure 2 in the appendix shows the distributions of spamcount and spamipcount across the top 300 most spam-facilitating ASes in our dataset, as well as the cumulative distribution of these same badness measures over our entire dataset. The graphs confirm that most of the spam in our dataset is generated by IP addresses from a small percentage of autonomous systems, consistent with many other measurement studies involving spam [11, 23–25, 34]. This feature offers justification for our focus on only a few of the worst offenders. The graphs also give a sense of the relationship between spamcount and spamipcount, showing that both measures follow similar distributions and are strongly correlated.

### 4.3 Targeting ASes with High Spamcount

Table 1 below gives the computed value of several metrics for each of the top five highest-ranked ASes by spamcount.

The spam ip to exclusive customer cone prefix size ratio is given in the table’s last column. As mentioned previously, this is our preferred metric for quantifying targetability. We see from the table that one particular autonomous system, ASN 45899, VPNT Corp, has a high score under this metric. It is a stub AS, with no customer ASes; it has a high badness score using both spamcount and spamipcount – in fact the spamcount is more than double that of any other AS in our entire dataset; and it does not have any

**Table 1.** ASes with the highest spamcount in our dataset

| ASN   | Organization Name              | Spam Count | Percent of Spam | Spam IP Count | Customer Cone Prefix Size | Exclusive Cust Cone Prefix Size | Spam IP to Prefix Size Ratio |
|-------|--------------------------------|------------|-----------------|---------------|---------------------------|---------------------------------|------------------------------|
| 45899 | VNPT Corp                      | 132918     | 7.9%            | 30222         | 12                        | 12                              | 2518                         |
| 4766  | Korea Telecom                  | 54237      | 3.2%            | 6833          | 203306                    | 2537                            | 2.7                          |
| 4134  | Chinanet Backbone              | 44482      | 2.7%            | 10360         | 66172                     | 1361                            | 7.6                          |
| 7738  | Telecomunicacoes da Bahia S.A. | 39570      | 2.4%            | 7904          | 111324                    | 518                             | 15.3                         |
| 4837  | China169 Backbone              | 36617      | 2.2%            | 8269          | 6438                      | 1664                            | 5.0                          |

counterbalancing large number of IP addresses or /24 prefixes in its exclusive customer cone.

The next few autonomous systems on the list have more exclusive customers and are generally much higher up in the internet tier hierarchy. The ratio metrics applied to these ASes is not nearly so high, by several orders of magnitude; and it would be more difficult to justify a targeting strategy for any of the next four ASes based on this metric.

Due to current limitations of our data on the badness side, our true proscription towards actually targeting VPNT Corp is perhaps not very strong. The intent of this paper is not to make targeting proscriptions, but rather to introduce and illustrate a useful methodology. We have shown that well-motivated targetability metrics can be computed and applied to real ASes, using plausible data, with interesting and highly variable results. As our badness measurements become better quantified with higher quality data, proscriptive targeting arguments can be supported on this basis.

#### 4.4 Discussion

What are the relative advantages of the different metrics? Our view is that it depends on the application and the quality of the datasets involved. The metrics invoking badness only at the IP level are more robust in the sense that they are less likely to change quickly over time, (since, for example, it may be easier to send additional spam messages from the same compromised IP address, then to compromise an additional IP address), and are also more applicable to the problem of diagnosing the source of badness. On the other hand, metrics equating badness with direct aggregate features such as raw spam volume are in better correspondence with the negative effects imposed on the rest of the network. In a similar fashion, metrics involving the *exclusive customer cone size* and *exclusive customer cone prefix size*, are more robust in the sense that they are less likely to change significantly if connectivity relations change by not too much. Further, if the data being used is accurate and not likely to change, then metrics involving the exclusive customer cone address size most directly correspond to the aggregate benefit to the network that would be lost if an autonomous system were targeted.

We want to emphasize that each of these metrics, based on exclusive customer cones, is a conservative metric, in the sense that the metric will generally paint an ISP as “less targetable” than it would be painted if more edges were included. This feature is important, as the connectivity data we use is approximate and is known to err on the side of omitting edges from the graph [10]. A practitioner might worry that targeting a particular AS might cause more collateral damage than expected. This would likely be the case if we used a metric based on customer cone. In such circumstance, an ISP who might otherwise be subject to targeting would have an incentive to simply add more customer edges to lower their disconnectability measure. But because we are using the exclusive customer cone, such a strategy would not be effective. Moreover, the customers of a bad AS would have the ability to adopt an alternative provider, resulting in a simultaneous decrease in target risk for the customer, and an increase in the disconnectability of the bad provider. The idea is that by publishing a metric, we create an incentive structure that tends to isolate the bad guys from the good guys. As miscreant behavior of an AS increases, the good guys have more and more of an incentive to line up an alternate provider, to avoid becoming collateral damage.

## 5 Conclusions and Future Work

Today’s spam problem involves many players with competing interests; and any solution requires numerous tradeoffs. In our study of this problem, we have focused our attention on the players we see as having the most power to resolve the problem, namely the ISPs. This approach has led us to an investigation of metrics applicable to ISP targeting through disconnection. Policy makers must consider a wide variety of technical, policy, and incentive-relevant challenges to realizing ISP disconnections in practice. Our contribution to this effort has involved demonstrating the tractability of developing an objective framework for addressing the problem.

Our goal is to continue advancing research on the prevention of Internet-related misbehavior through the publication of metrics that can affect an ISP’s reputation. We consider our program as parallel to more direct technological approaches for combatting spam, such as botnet targeting and spam filtering. By developing an objective framework for considering ISP targeting through disconnection, we advance the tools available to economic researchers for use in the modeling of the Internet ecosystem, and help to foster a better understanding of the problem from crucial perspectives.

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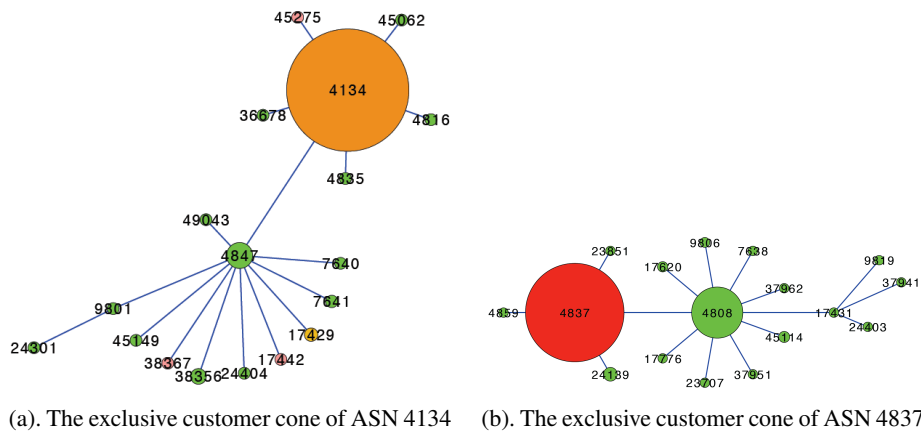
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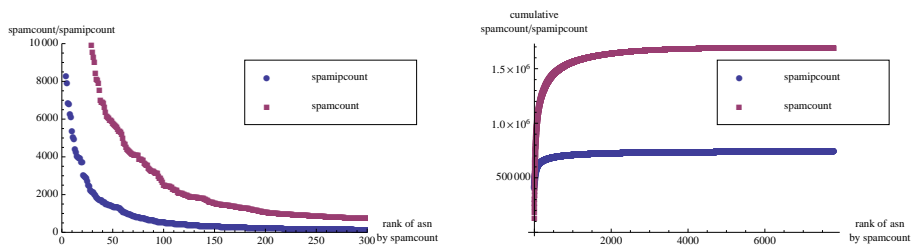
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## A Appendix





**Fig. 1.** The size of each node relates linearly to its spamcount. The color of each node relates to the ratio of its spamcount to its individual prefix size.



**Fig. 2.** The ASNs in order by spamcount.