

# Understanding Botnet-driven Blog Spam: Motivations and Methods

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## Introduction

Spam, or unsolicited commercial communication, has evolved from telemarketing schemes to a highly sophisticated and profitable black-market business. Although many users are aware that email spam is prominent, they are less aware of blog spam (Thomason, 2007). Blog spam, also known as forum spam, is spam that is posted to a public or outward facing website. Blog spam can be to accomplish many tasks that email spam is used for, such as posting links to a malicious executable.

Blog spam can also serve some unique purposes. First, blog spam can influence purchasing decisions by featuring illegitimate advertisements or reviews. Second, blog spam can include content with target keywords designed to change the way a search engine identifies pages (Geerthik, 2013). Lastly, blog spam can contain link spam, which spams a URL on a victim page to increase the inserted URLs search engine ranking. Overall, blog spam weakens search engines' model of the Internet popularity distribution. Much academic and industrial effort has been spent to detect, filter, and deter spam (Dinh, 2013), (Spirin and Han, 2012).

Less effort has been placed in understanding the underlying distribution mechanisms of spambots and botnets. One foundational study in characterizing blog

spam (Niu et al., 2007) provided a quantitative analysis of blog spam in 2007. This study showed that blogs in 2007 included incredible amounts of spam but does not try to identify linked behavior that would imply botnet behavior. A later study on blog spam (Stringhini, 2015) explores using IPs and usernames to detect botnets but does not characterize the behavior of these botnets. In 2011, a research team (Stone-Gross et al., 2011) infiltrated a botnet, which allowed for observations of the logistics around botnet spam campaigns. Overall, our understanding of blog spam generated by botnets is still limited.

## Related Work

Various projects have attempted to identify the mechanics, characteristics, and behavior of botnets that control spam. In one important study (Shin et al., 2011), researchers fully evaluated how one of the most popular spam automation programs, XRumer, operates. Another study explored the behavior of botnets across multiple spam campaigns (Thonnard and Dacier, 2011). Others (Pitsillidis et al., 2012) examined the impact that spam datasets had on characterization results. (Lumezanu et al., 2012) explored the similarities between email spam and blog spam on Twitter. They show that over 50% of spam links from emails also appeared on Twitter.

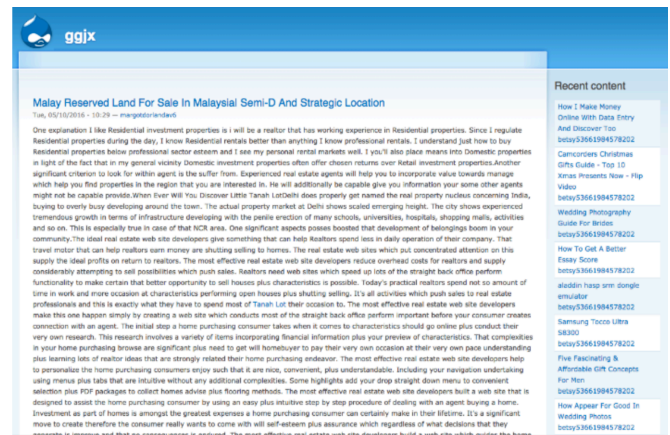


Figure 1: Browser rendering of the ggjx honeypot

The underground ecosystem build around the botnet community has been explored (Stone-Gross et al., 2011). In a surprising result, over 95% of pharmaceuticals advertised in spam were handled by a small group of banks (Levchenko et al., 2011). Our work is similar in that we are trying to characterize the botnet ecosystem, focusing on the distribution and classification of certain spam producing botnets.

## Experimental Design

In order to classify linguistic similarity and differences in botnets, we implement 3 honeypots to gather samples of blog spam. We configure our honeypots identically using the Drupal content management systems (CMS) as shown in Figure 1. Our honeypots are identical except for the content of their first post and their domain name. Ggix.org is fashion themed, npcagent.com is sports themed, and gjams.com is pharmaceutical themed. We combine the data collected from Drupal with the Apache server logs (Apache, 2016) to allow for content analysis of data collected over 42 days. To allow botnets time to discover the honeypots, we activate the honeypots at least 6-weeks before data collection.

We generate three tables of content for each honeypot (Bevans and Khosmood, 2016). In the user table, we record the information the spambot enters while registering and user login statistics that we summarize in Table 1. This includes the user id, username, password, date of registration, registration IP, and number of logins. In the content table, we record the content of spam posts and comments which we summarize in Table 2. This includes the blog node id, the author’s unique id, the date posted, the number of hits, type of post, title of the post, text of the post, links in the post, language of the post, and a taxonomy of the post from IBM’s Alchemy API.

Honeypot	Quantity	Mean Logins/User	# of Countries
ggjx	62992	1.066	83
gjams	28230	1.102	40
npcagent	34332	1.05	53

Table 1: User table characteristics for three honeypots

Honeypot	Quantity	Avg. Hits	Avg. Links	English Posts
ggjx	2279	28.237	2.356	1962
gjams	2225	18.178	0.311	2137
npcagent	1430	29.043	1.823	1409

Table 2: Characteristics for the content tables

Honeypot	ggjx	gjams	npcagent
# Of Entities	3430	1790	1566
# of Users	62992	28230	34332
Mean Users/Entity	18.365	15.771	21.923
Max Users/Entity	37589	14249	23577
$\sigma$ of Users/Entity	666.128	359.619	611.157
# of IPs	5291	3092	2120
Mean IPs/Entity	1.543	1.727	1.354
Maximum IPs/entity	118	135	60
$\sigma$ of IP Quantity	4.277	5.551	2.406
Mean Posts/Entity	.664	1.243	.907
Max Posts/Entity	163	484	664
$\sigma$ of Posts/Entity	5.319	14.448	17.256
% of Entities Who Posted	15.2	12.4	13.5

Table 3: Characteristics of entities

Lastly, in the access table, we include data and meta-data from the Apache logs. This includes the user id, the access IP, the URL, the HTTP request type, the node ID, and an action keyword describing the type of access.

Our honeypots received a total of 1.1 million requests for ggjx, 481 thousand requests for gjams, and 591 thousand requests for npcagent.

## Entity Reduction

It is widely accepted that spambot networks, or botnets, are responsible for most spam. Therefore, we algorithmically reduce spam instances into unique entities representing botnets. For each entity, we define 4 attributes: entity id, associated IPs, usernames, and associated user ids. To construct entities we scan through the users and assign each one to an entity as follows.

1. For a user, if an entity exists which contains its username or IP, the user is added to the entity.
2. If more than one entity matches the above criteria, all matching entities are merged.
3. If no entity matches the above criteria, a new entity is created.

We summarize the entity characteristics in Table 3. The maximum number of users in one entity is almost 38 thousand for ggjx with over 100 unique IP addresses. These results confirm what is expected - the vast majority of bots interacting with our honeypots are part of large botnets. This also allows us to perform content analysis exploring what linguistic qualities differentiate botnets.

Feature	Description	Indicates	Effective
Bag or Words	Set of words with count	Lexical content	Yes
Alchemy	Document taxonomy	Taxonomy	Yes
Link	URL core domain names	URL similarity	Variable
Vocab	Vocab complexity	Vocabulary complexity	No
Part-of-speech	A BoW of parts-of-speech	Simple syntax	No

Table 4: NLP feature sets we consider for our content analysis and their effectiveness at differentiating botnets

## Content Analysis

To better understand botnets, we use natural language processing (Collobert and Weston, 2008) for analyzing the linguistic content of entities. For our analysis, we consider various feature sets as proxies for linguistic characteristics as summarized in Table 4. We use a Maximum Entropy classifier (Mega M, 2016) to test which features differentiate botnets. In order to test a feature, we train the classifier with 70% of the posts, randomly selected, from the N largest entities

and test it with the remaining 30% of the posts. Our final results are the average of three runs.

The first feature set we test is Bag Of Words (BoW) which models the lexical content of posts. Put simply, each word in a document is put into a ‘bag’ and the syntactic structure is discarded. For implementation details, see our technical report (Bevans, 2016). In Figure 2, we show our analysis of the BoW feature set.

When considering the top 5 contributing entities, the classification accuracy is less than 95% which implies that the lexical content of botnets varies greatly. The second feature we consider is the taxonomy provided by IBM Watson’s AlchemyAPI. Alchemy’s output is a list of taxonomy labels and associated confidences. For the purpose of our analysis, we discard any low or non-confident labels. In Figure 3, we show our analysis of the Alchemy Taxonomy feature set which highlights the accuracy of Alchemy’s taxonomy. We note that the Alchemy Taxonomy feature set is dramatically smaller in size than the BoW feature set while still providing high performance. This indicates a full lexical analysis is not necessary but a taxonomic approach is sufficient. Our third feature is based on the links in the posts. To create the feature, we parse each post for any HTTP links and strip the link to its core domain name.

The classifier with the link feature set had varied results, as shown in Table 5, where it was reliable in differentiating ggjx entities but less reliable for the other two honeypots. These results correlate with link scarcity from Table 2.

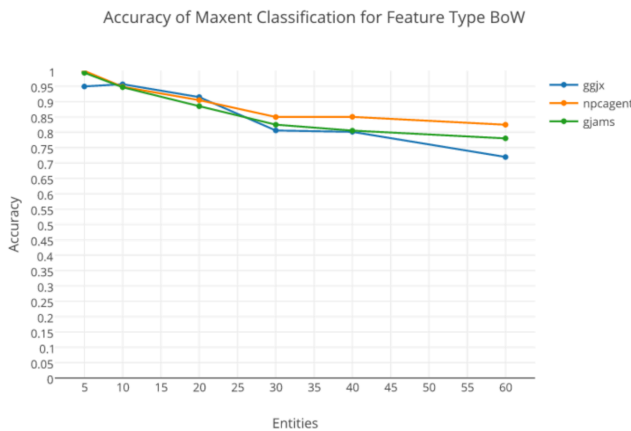


Figure 2

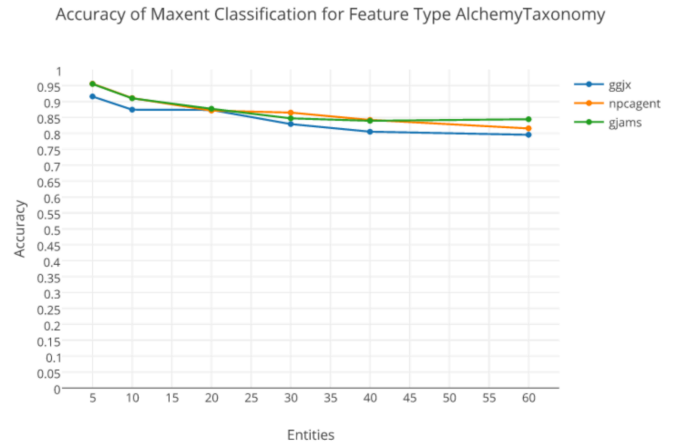


Figure 3

We test the normalized vocabulary size of a post as a feature. We derive this from the number of unique words divided by the total number of words in the post. As shown in Table 5, the vocabulary size does not differentiate botnets.

We also form a feature set based on the part-of-speech (PoS) makeup of a post using the Stanford PoS Tagger. The Stanford PoS tagger returns a pair for each word in the text, the original word and corresponding PoS. We create a BoW from this response that creates an abstract representation of the document’s syntax. As shown in Table 5, the PoS does not differentiate botnets.

Feature Set	Database	Accuracy (10 entities)	Accuracy (60 entities)
BoW	ggjx	93%	71%
BoW	gjams	92%	78%
BoW	npcagent	93%	83%
Alchemy	ggjx	87%	80%
Alchemy	gjams	91%	84%
Alchemy	npcagent	91%	82%
Link	ggjx	89%	84%
Link	gjams	53%	37%
Link	npcagent	72%	61%
PoS	ggjx	32%	16%
PoS	gjams	53%	39%
PoS	npcagent	70%	60%
Vocab	ggjx	32%	17%
Vocab	gjams	50%	36%
Vocab	npcagent	74%	60%

Table 5: Accuracies for various features when identifying 10 and 60 entities using the maximum entropy classifier

## Conclusions

In this paper, we examine interesting characteristics of spam-generating botnets and release a novel corpus to the community. We find that hundreds of thousands of fake users are created by a small set of botnets and much fewer numbers of them actually post spam. The spam that is posted is highly correlated by subject language to the point where botnets labeled

by their network behavior are to a large degree re-discoverable using content classification (Figure 3).

While link and vocabulary analysis can be good differentiators of these botnets, it is the content labeling (provided by Alchemy) that is the best indicator. Our experiment only spans 42 days, thus it's possible the subject specialization is a feature of the campaign rather than the botnet itself.

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