ABSTRACT
Like other social media websites, YouTube is not immune from the attention of spammers. In particular, evidence can be found of attempts to attract users to malicious third-party websites. As this type of spam is often associated with orchestrated campaigns, it has a discernible network signature, based on networks derived from comments posted by users to videos. In this paper, we examine examples of different YouTube spam campaigns of this nature, and use a feature selection process to identify network motifs that are characteristic of the corresponding campaign strategies. We demonstrate how these discriminating motifs can be used as part of a network motif profiling process that tracks the activity of spam user accounts over time, enabling the process to scale to larger networks.

Categories and Subject Descriptors
C.2.0 [Computer-Communication Networks]: General – Security and protection; H.3.5 [Online Information Services]: Web-based services

General Terms
Experimentation, Security

Keywords
Spam, YouTube, network motif analysis, social network analysis

1. INTRODUCTION
The popularity and success of YouTube, a video-sharing website consisting for the most part of user-generated content, continues to grow. Recent statistics report that it now receives more than four billion video views per day, with sixty hours of video being uploaded every minute; increases of 30% and 25% respectively over the prior eight months. However, as is the case with many other high-profile social media websites, YouTube has attracted unwelcome attention from spammers. In this paper, we are concerned with the facility that permits users to post comments to videos, thus providing a mechanism that can be used to propagate spam messages. This can be achieved with relative ease given the availability of bots that are used to post comments in large volumes. It is important at this point to distinguish between promoters and spammers, with the former using such tools to encourage channel or video views, whereas the general objective of the latter is to entice users to visit malicious third-party websites.

One of the findings of our previous work was the discovery of orchestrated campaigns targeting popular YouTube videos with bot-posted spam comments. These campaigns are often of a recurring nature, operating with periodic bursts of activity on a continual basis. It appears that different campaign strategies are in use, for example, a large number of user accounts each commenting on a small number of videos, or a small number of accounts each comment-
ing on many videos. An example of a campaign using the latter strategy can be seen in Figure 1 taken from a network derived from comments posted by users to videos within a particular time period.

Our approach uses the concept of network motif profiling [17,16,25] to detect the recurring activity of these spam campaigns, where motif counts from the derived networks are tracked over time. Motifs are enumerated on an egocentric basis, where an ego is a single user node within the networks, and the resulting profiles of motif counts can be used for user characterization in order to detect spam activity. Our strategy has been to consider all motifs because we don’t assume any prior knowledge of the nature of spam campaigns and motifs that might be characteristic of spammers.

However, the enumeration of all motif instances present in the user networks can be a lengthy process. At the same time, we have found that certain discriminating motifs may be used to identify particular strategies and the associated users as they periodically recur. Given this, the objective of this paper is to determine from a preliminary analysis a discriminating subset of motifs for profiling, so that the resulting improvement in performance would permit its application to larger networks.

This paper begins with a description of related work in the domain. Next, the methodology used by the detection approach is described in detail, from derivation of the comment-based networks to the subsequent network motif profile generation. We describe the feature selection process used to identify a set of discriminating motifs, using profiles associated with known spam user accounts. Results are then presented from an evaluation of the modified process where only these motifs are considered. This evaluation focuses on performance improvement and the detection effectiveness. Finally, the overall conclusions are discussed, and some suggestions for future work are made.

2. RELATED WORK

2.1 Structural and spam analysis

The structure of YouTube has been analyzed in a number of separate studies. Cha et al. [7] performed an extensive study that focused on popularity distribution and evolution, content distribution and the prevalence of duplication and illegal uploads. Paolillo et al. [20] investigated the social structure with the generation of a user network based on the friendship relationship, focusing on the degree distribution. They found that YouTube is similar to other online social networks with respect to degree distribution, and that a social core exists between authors (uploaders) of videos. An alternative network based on related videos was analyzed by Cheng et al. [8]. Given that the resulting networks were not strongly connected, attention was reserved for the largest strongly connected components. These components were found to exhibit small-world characteristics [23], with large clustering coefficients and short characteristic path lengths, indicating the presence of dense clusters of related videos.

Benevenuto et al. [3] created a directed network based on videos and their associated responses. Similarly, they found that using the largest strongly connected components was more desirable due to the large clustering coefficients involved. This was a precursor to subsequent work concerned with the detection of spammers and content profilers within YouTube [5,14]. Features from the video responses networks (e.g. clustering coefficient, reciprocity) were used as part of a larger set to classify users accordingly. Other YouTube spam investigations include the recent work of Sureau [22], based on the detection of spam within comments posted to videos. A number of features were derived to analyze the overall activity of users, rather than focusing on individual comment detection.

An extensive body of work has been dedicated to the analysis of spam within other online social media sites. For example, Mishne et al. [18] suggested an approach for the detection of link spam within blog comments using the comparison of language models. Han et al. [12] investigated the use of a collaborative spam filtering scheme to block link spams in blogs. Gao et al. [10] investigated the proliferation of spam within Facebook “wall” messages, with the detection of spam clusters using networks based on message similarity. This particular study demonstrated the bursty (recurring) and distributed aspects of botnet-driven spam campaigns, as discussed by Xie et al. [26]. The shortcomings of URL blacklists for the prevention of spam on Twitter were highlighted by Grier et al. [11], where it was found that blacklist update delays of up to twenty days can occur. This is a particular problem with the use of shortened URLs, the nature of which was also analyzed by Chhabra et al. [9]. The long-term study by Lee et al. [15] involved the deployment of Twitter honeypots that resulted in the harvesting of 36,000 candidate content polluters.

2.2 Network motif analysis

*Network motifs* [17,21] are structural patterns in the form of interconnected $n$-node subgraphs that are considered to be inherent in many varieties of network, such as biological, technological and sociological networks. They are often used for the comparison of said networks, and can also indicate certain network characteristics. In particular, the work of Milo et al. [16] proposed the use of *significance* profiles based on the motif counts found within networks to enable the comparison of local structure between networks of different sizes. In this case, the generation of an ensemble of random networks was required for each significance profile. An alternative to this approach [25] involved the use of motif profiles that did not entail random network generation. Instead, profiles were created on an egocentric basis for the purpose of characterizing individual egos, encompassing the motif counts from the entirety of egocentric networks within a particular network.

The domain of spam detection has also profited from the use of network motifs or subgraphs. Within a network built from email addresses [6], a low clustering coefficient (based on the number of triangle structures within a network) may indicate the presence of spam addresses, with regular addresses generally forming close-knit communities, i.e. a relatively higher number of triangles. Becchetti et al. [2] made use of the number of triangles and clustering coefficient as features in the detection of web spam. These two features were found to rank highly within an overall feature set. Motifs of size three (triads) have also been used to detect spam comments in networks generated from blog interaction [13]. It was found that certain motifs were likely to indicate the presence of spam, based on comparison with corresponding random network ensembles.

Separately, network motifs have also been used to char-
acterize network traffic \cite{1}. A network was created for each application (e.g. HTTP), and nodes within the network were classified using corresponding motif profiles.

3. YOUTUBE COMMENT NETWORKS

3.1 Comment processing and network generation

In our previous work \cite{9}, we described the collection of a data set that was undertaken in order to investigate contemporary spam comment activity within YouTube. We opted for a specific selection of the available data given that spam comments in YouTube tend to be directed towards a subset of the entire video set, i.e. more popular videos generally have a higher probability of attracting attention from spammers, thus ensuring a larger audience. A decision was made to use only data to which access was not restricted, namely the comments posted to videos along with the associated user accounts. To facilitate our objective of analyzing recurring spam campaigns, we periodically retrieved the details and comments of popular videos on a continual basis, using the Most Viewed standard feed provided by the YouTube Data API.\footnote{The data set is available at \url{http://mlg.ucd.ie/yt}} The API also provides a spam hint property within the video comment meta-data, which is set to true if a comment has previously been marked as spam. However, this property cannot be considered reliable due to its occasional inaccuracy, where innocent comments can be marked as spam, while obvious spam comments are not marked as such.

Our methodology requires the generation of a network to represent the comment posting activity of users to a set of videos. Initially, comments made during a specified time interval are selected from the data set described above. To counteract obfuscation efforts by spammers in order bypass their detection by any filters, a number of pre-processing steps must then be executed. During this process, each comment is converted to a set of tokens, followed by the removal of stopwords along with any non-Latin-based words, as the focus of this evaluation is English-language spam comments. Punctuation characters are also removed, and letters are converted to lowercase. A modified comment text is then generated from the concatenation of the generated tokens.

As initial analysis found that spam comments can often be longer than regular comments, any texts shorter than a minimum length (currently 25 characters) are removed at this point. Although the campaign strategies under discussion here are concerned with attracting users to remote sites through the inclusion of URLs in comment texts, comments without URLs are currently retained. This ensures the option of analyzing other types of spam campaigns, such as those encouraging channel views, i.e. promoters\footnote{http://code.google.com/apis/youtube/gettingStarted.html#data_api}, along with the behaviour of regular users.

A network can then be generated from the remaining modified comment texts. This network consists of two categories of node, users and videos. An undirected edge is created between a user and a video if at least one comment has been posted by the user on the video, where the edge weight represents the number of comments in question. For the moment, the weight is merely recorded but is not subsequently used when counting motifs within the network. To capture the relationship between the users involved in a particular spam campaign, undirected and unweighted edges are created between user nodes based on the similarity of their associated comments. Each modified (tokenized) comment text is converted to a set of hashes using the Rabin-Karp rolling hash method\footnote{http://code.google.com/apis/youtube/gettingStarted.html#data_api}, with a sliding window length of 3. A pairwise distance matrix, based on Jaccard distance, can then be generated from these comment hash sets. For each pairwise comment distance below a threshold (currently 0.6), an edge is created between the corresponding users if one does not already exist.

Afterwards, any users whose set of adjacent nodes consists solely of a single video node are removed. Since these users have commented on only one video, and are in all likelihood not related to any other users, they are not considered to be part of any spam campaign. The resulting network tends to consist of one or more large connected components, with a number of considerably smaller connected components based on videos with a relatively minor amount of comment activity. Finally, an approximate labelling of the user nodes is performed, where users are labelled as spam users if they posted at least one comment whose spam hint property is set to true. All remaining users are labelled as regular users. Although this can lead to label inaccuracies, the results shown later in this paper demonstrate that such inaccuracies will be perceivable.

3.2 Network motif profiles

Once the network has been generated, a set of egocentric networks can be extracted. In this context, given that the focus is on user activity, an ego is a user node, where its egocentric network is the induced $k$-neighbourhood network consisting of those user and video nodes whose distance from the ego is at most $k$ (currently 2). Motifs from size three to five within the egocentric networks are then enumerated using FANMOD\footnote{http://code.google.com/apis/youtube/gettingStarted.html#data_api}. A set of motif counts is maintained for each ego, where a count is incremented for each motif instance found by FANMOD that contains the ego. A network motif count profile is then created for each ego. As the number of possible motifs can be relatively large (particularly if directed and/or weighted edges are considered), the length of this profile will vary for each network generated from a selection of comment data, rather than relying upon a profile with a (large) fixed length. For a particular generated network, the profiles will contain an entry for each of the unique motifs found in the entirety of its constituent egocentric networks. Any motifs not found for a particular ego will have a corresponding value of zero in the associated motif profile.

As mentioned previously, the work of Milo et al.\footnote{http://code.google.com/apis/youtube/gettingStarted.html#data_api} proposed the generation of a significance profile, where the significance of a particular motif was calculated based on its count in a network along with that generated by an ensemble of corresponding random networks. These profiles then permitted the subsequent comparison of different networks. In this work, the egocentric networks are compared with each other, and the generation of random ensembles is not performed. An alternative ratio profile $r_p$\footnote{http://code.google.com/apis/youtube/gettingStarted.html#data_api} is created for each ego, where the ratio value for a particular motif is based on the counts from all of the egocentric networks, i.e.:
Having confirmed these users as belonging to the spam campaigns by analyzing their posted comments, two training sets were created. These sets contained the normalized ratio profiles for both the respective spam campaign users and the regular users in the selected time windows. To avoid any interference from other potential spam campaigns or individual spam users, any other spam users active in the window (i.e. those who had at least one comment marked as spam) were removed in both cases. Although the possibility exists for spam users not to be marked accordingly due to the inconsistency of the spam hint property, it was felt that the percentage of regular users that may in fact have been spam users would be relatively minor and so no further filtering was performed.

A third spam campaign (Campaign 3) was also active in this seventy-two hour period. Its strategy appeared to use a large number of users to each post almost identical messages to a small (~1) number of videos. It did not have the same frequency as the other campaigns (it was not as prevalent in the data set as the other two), but given the vast number of spam accounts involved it was felt to be worthy of consideration due to the potential addition of further discriminating motifs. As before, a third training set containing a set of spam and regular users for a particular window was created.

### 4.1 Identifying Typical Spam Accounts

In our previous work [19], we performed an experiment that tracked two spam campaigns which we had discovered following manual analysis of the data set. Two distinct campaign strategies were in use, i.e. a small number of accounts each commenting on many videos (Campaign 1), and a larger number of accounts each commenting on few videos (Campaign 2). The experiment was run over a period of seventy-two hours, starting on November 14th, 2011 and ending on November 17th, 2011. In order to track the campaign activity over this period, the data set was split into twelve windows of six hours each. For each of these windows, a network of user and video nodes was derived using the process described in the previous section. A normalized ratio profile was generated for each ego (user), based on the motif counts of the corresponding egocentric network. Principal components analysis (PCA) was then performed on these profiles to produce 2-dimensional spatializations of the user nodes, using the first two components. These spatializations acted as the starting point for the analysis of activity within the twelve time windows.

Although the comment spam hint property was used to assist manual analysis, the previous work was an unsupervised exercise in that no formal labelled training set was generated. In order to determine a set of discriminating motifs for this paper, a training set with labelled data was required. For this purpose, we identified time windows containing the highest number of users belonging to the two campaigns. This was achieved by initially locating suspicious (outlier) users in the PCA spatializations (e.g. see Figure 4). In particular, we paid closest attention to those spatializations where the visible separation was greatest between the outliers and the majority of regular users.

Having confirmed these users as belonging to the spam campaigns by analyzing their posted comments, two training sets were created. These sets contained the normalized ratio profiles for both the respective spam campaign users and the regular users in the selected time windows. To avoid any interference from other potential spam campaigns or any interference from other potential spam campaigns or the regular users in the selected time windows.

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#### 4.2 Feature Selection

Having generated the labelled training sets, we ranked the features (motifs) using information gain to determine those that would be characteristic of the classes of interest. Due to the nature of the campaigns, the training sets contained a relatively small number of campaign spam users compared with that of regular users. To cater for this, we generated random samples from the training sets by specifying the maximum distribution spread of both classes. Different ratios of regular users to spam users were available for the three campaigns, given that varying numbers of users are involved. Those ratios that generated the highest information gain were chosen. Details of the instance samples can be found in Table 1.

| Campaign | 1   | 2   | 3   |
|----------|-----|-----|-----|
| Motifs   | 158 | 159 | 158 |
| Regular:Spam ratio | 5.1 | 3.1 | 2.1 |
| Regular instances | 30  | 66  | 136 |
| Spam instances    | 6   | 22  | 68  |

Table 1: Campaign training set samples

A plot of the motif rankings and corresponding information gain using the training set samples can be seen in Figure 2.

Figure 2: Information gain rankings

\[
rp_i = \frac{\text{nmp}_i - \text{mmp}_i}{\text{nmp}_i + \text{mmp}_i + 1}
\]

Here, nmp\(_i\) is the count of the \(i^{th}\) motif in the ego’s motif profile, mmp\(_i\) is the average count of this motif for all motif profiles, and \(\epsilon\) is a small integer that ensures that the ratio is not misleadingly large when the motif occurs in only a few egocentric networks. To adjust for scaling, a normalized ratio profile \(\text{nrp}\) is then created for each ratio profile \(rp\) with:

\[
\text{nrp}_i = \frac{rp_i}{\sqrt{\sum rp^2_j}}
\]
A selection of 21 motifs was made from those that generated the highest information gain values, 7 for each of the three campaigns. These motifs can be found in Table 2. The selection was straightforward for campaign 3, as it was merely a case of selecting the 7 most highly-ranked motifs. However, as can be seen in Figure 2, a relatively large number of motifs were found to generate the highest information gain value for both campaigns 1 and 2. In both cases, we analyzed those motifs ranked highest, and made a selection based on our knowledge of the campaign strategies following manual analysis of the data set. For example, campaign 1 uses a small number of users commenting on a large number of videos, and so those motifs containing more user-video edges have been selected. For campaign 2, motifs have been selected that highlight the fact that users appear to be more likely to be connected to other users rather than videos. The strategy of this campaign is to employ a larger number of users, each commenting on a small number of videos, and the potential for connectivity between users is higher given the similarity of their comments. These motifs also reflect the observed behaviour of users in the campaign often not commenting on the same videos, as no two users share a video node neighbour.

| Window | Video nodes | User nodes (spam) | Edges |
|--------|-------------|-------------------|-------|
| 1      | 322         | 903 (222)         | 2974  |
| 2      | 335         | 559 (163)         | 1446  |
| 3      | 282         | 745 (157)         | 2087  |
| 4      | 283         | 932 (249)         | 2475  |
| 5      | 291         | 794 (214)         | 2848  |
| 6      | 269         | 470 (123)         | 1222  |
| 7      | 281         | 759 (190)         | 1931  |
| 8      | 282         | 976 (231)         | 2491  |
| 9      | 300         | 689 (163)         | 1795  |
| 10     | 330         | 551 (136)         | 1701  |
| 11     | 292         | 826 (168)         | 2586  |
| 12     | 302         | 958 (225)         | 2995  |

Table 3: Network details for all six-hour windows from December 29th, 2011 to January 1st, 2012.

An analysis of the resulting PCA spatializations found that campaigns 1 and 2 were regularly active during this period. Other spam activity can also be seen, ranging from an abundance of channel promotion messages from individual users, to other smaller-scale campaigns. To demonstrate the effect of using a subset of discriminating motifs, a period of seventy-two hours has been chosen where campaigns

5. EVALUATION

5.1 Optimization using discriminating motifs

Having selected the 21 discriminating motifs, a series of experiments were run to analyze the spam activity within the collected data set. For the purpose of this evaluation, the experiments were focused upon tracking any campaigns having similar strategies to those mentioned in the previous section, i.e. a small number of accounts each commenting on many videos (Campaign 1), and variants on a larger number of accounts each commenting on few videos (Campaigns 2 and 3). The period from December 1st, 2011 to January 16th, 2012 was split into windows of six hours each. For each of these windows, a network of user and video nodes was derived using the process described earlier, and a normalized ratio profile was generated for each ego (user), based on the motif counts of the corresponding egocentric network. In this case however, only the 21 discriminating motifs were enumerated. Following principal components analysis of these profiles, the spatializations of the first two principal components act as the starting point for the analysis of activity within the set of time windows.

As FANMOD [24] normally enumerates all motifs of a particular size found within a specified network, a modification to the source code was required in order to permit a subset of required motifs to be also specified. We modified the command-line version to accept a set of motif identifiers as an additional input parameter. The enumeration algorithm remains unchanged, instead, the specified motif identifiers are used to filter the FANMOD output; any instances found for motifs that are not members of this set are discarded. As we perform additional post-processing of the enumerated motif instances, this filtering results in a noticeable improvement in performance.

http://theinf1.informatik.uni-jena.de/~wernicke/motifs/
1 and 2 were active, starting on December 29th, 2011 and ending on January 1st, 2012. The network details for the twelve six-hour windows can be found in Table 3.

For each of the networks in this period, FANMOD was executed once having specified the selected 21 motifs, and once without specifying required motifs (all motifs were enumerated). Figure 3 contains a plot of the FANMOD and associated post-processing execution times for each window. As might be expected, there is a noticeable difference in times between the specification of the selected motifs, and the case where all motifs are enumerated. On average, the execution is faster by a factor of 3 when the discriminating motifs are specified.

### 5.2 Effectiveness

The objective of this section is to demonstrate the effectiveness of the discriminating motifs in the detection of spam campaigns. As the PCA spatializations are used as the starting point for any analysis, this will be addressed through the comparison of two spatializations for Window 5 (12am to 6am, December 30th, 2011); one created using the normalized ratio profiles generated from the enumeration of the selected 21 motifs, and the other with profiles generated from all motifs within the network. These spatializations can be seen in Figure 4.

At a glance, both spatializations look extremely similar, as expected given the high correlation between the motifs. Here, users posting at least one comment marked as spam (using the spam hint property) are in red, all other users are in orange. The points corresponding to the spam campaign users have been highlighted accordingly. In both cases, it can be seen that:

1. The vast majority of users are regular, and appear as overlapping points at the top of the leftmost cluster.
2. There is a clear distinction between the two different campaign strategies, as these points are plotted separately (both from regular users and each other).
3. The inaccuracy of the *spam hint* comment property is demonstrated as the Campaign 2 cluster contains users not coloured in red, i.e. none of their comments were marked as spam. Similarly, the reverse is true with the large cluster of regular users in that it contains a certain number of users coloured in red.

Apart from the highlighted campaign clusters, other spam nodes in the spatializations have been correctly marked as such. For example, those users towards the bottom-left appear to be mostly individual spam accounts having similar behaviour to the strategy of Campaign 1, but on a smaller scale. They include users encouraging channel views, i.e. *promoters*[^4], and also a number of users belonging to a separate campaign. Given the similarity of the spatializations, we can assume that the use of a subset of discriminating motifs in campaign detection can be just as effective as

[^4]: *promoters*
6. CONCLUSIONS AND FUTURE WORK

The presence of orchestrated spam campaigns can be detected in YouTube, where sets of spam accounts are used to periodically post comments to popular videos. These campaigns can employ different strategies, for example, a large number of user accounts each commenting on a small number of videos, or a small number of accounts each commenting on many videos. In this paper, having derived networks from comments posted by users to videos within a set of time periods, we have characterized sets of user accounts using a network motif profiling process, where motifs are enumerated on an egocentric basis. Rather than enumerating all motifs within the constituent egocentric networks, we have found that characterization is also possible with a subset of these motifs. We have used a feature selection process to select sets of discriminating motifs associated with campaign strategies within the data set. Our results from enumerating these particular motifs on networks from later time periods have demonstrated that their detection of spam user accounts can be just as effective as that achieved when all motifs are used. At the same time, the resulting improvement in performance suggests that the use of discriminating motifs would be appropriate for larger networks, as the enumeration of all motifs can be a lengthy process. The results also demonstrate the recurring nature of these campaigns.

In this paper, we have identified three campaign strategies along with their corresponding discriminating motifs. In the future, it will be useful to identify other strategies that are present in the data set. For example, we have found evidence of other campaigns that tend to vary their strategies over time. This can lead to difficulties in detection, given that their behaviour can occasionally be similar to that of regular users. Apart from identifying further discriminating motifs, the current process may need to be modified to accommodate these strategies. Another possibility for future work is the derivation of other network representations from the data set, as the comments network used in this paper is just one abstraction of the underlying network structure.

7. ACKNOWLEDGMENTS

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Figure 5: Spatialization of the normalized ratio profiles for Window 5 (12am to 6am, December 30th, 2011) using motifs 4 and 12 from Table 2 (same colour coding as Figure 4). Although both campaigns are separated, most of the other spam users have now moved to the cluster of regular users in the top-left.
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