PeerRush: Mining for Unwanted P2P Traffic

Babak Rahbarinia[1], Roberto Perdisci[1] Andrea Lanzi[2], and Kang Li[1]

[1] Dept. of Computer Science, University of Georgia, Athens, GA 30602, USA,
babak,perdisci,kangli@cs.uga.edu
[2] EURECOM Institute, Sophia Antipolis, France,
lanzi@eurecom.fr

Abstract. In this paper we present PeerRush, a novel system for the identification of *unwanted* P2P traffic. Unlike most previous work, PeerRush goes beyond P2P traffic detection, and can accurately *categorize* the detected P2P traffic and attribute it to specific P2P applications, including malicious applications such as P2P *botnets*. PeerRush achieves these results without the need of deep packet inspection, and can accurately identify applications that use encrypted P2P traffic.
We implemented a prototype version of PeerRush and performed an extensive evaluation of the system over a variety of P2P traffic datasets. Our results show that we can detect all the considered types of P2P traffic with up to 99.5% true positives and 0.1% false positives. Furthermore, PeerRush can attribute the P2P traffic to a specific P2P application with a misclassification rate of 0.68% or less.

Keywords: P2P, Traffic Classification, Botnets

1 Introduction

Peer-to-peer (P2P) traffic represents a significant portion of today's global Internet traffic [13]. Therefore, it is important for network administrators to be able to identify and categorize P2P traffic crossing their network boundaries, so that appropriate fine-grained network management and security policies can be implemented. In addition, the ability to categorize P2P traffic can help to increase the accuracy of network-based intrusion detection systems [6].

While there exists a vast body of work dedicated to P2P traffic detection [4], a large portion of previous work focuses on signature-based approaches that require deep packet inspection (DPI), or on port-number-based identification [17, 7]. Because modern P2P applications avoid using fixed port numbers and implement encryption to prevent DPI-based detection [13], more recent work has addressed the problem of identifying P2P traffic based on statistical traffic analysis [10, 11]. However, very few of these studies address the problem of P2P traffic categorization [9], and they are limited to studying only few types of non-encrypted P2P communications. Also, a number of previous studies have focused on detecting P2P botnets [5, 22, 15, 2, 23], but with little or no attention to accurately distinguishing between different types of P2P botnet families based on their P2P traffic patterns.

In this paper, we propose a novel P2P traffic categorization system called PeerRush. Our system is based on a generic classification approach that leverages high-level statistical traffic features, and is able to accurately detect and categorize the traffic generated by a variety of P2P applications, including common file-sharing applications such as μTorrent, eMule, etc., P2P-based communication applications such as Skype, and P2P-botnets such as Storm [8], Waledac [16], and a new variant of Zeus [12] that uses encrypted P2P traffic. We would like to emphasize that, unlike previous work on P2P-botnet detection, PeerRush focuses on accurately detecting and **categorizing different types of legitimate and malicious P2P traffic**, with the goal of identifying *unwanted* P2P applications within the monitored network. Depending on the network's traffic management and security policies, the unwanted applications may include P2P-botnets as well as certain specific legitimate P2P applications (e.g. some file-sharing applications). Moreover, unlike most previous work on P2P-botnet detection, **PeerRush can reveal if a host is compromised with a specific P2P botnet type** among a set of previously observed and modeled botnet families. To the best of our knowledge, no previous study has proposed a generic classification approach to accurately detect and categorize network traffic related to both legitimate and malicious P2P applications, including popular applications that use encrypted P2P traffic, and different types of P2P-botnet traffic (encrypted and non-encrypted).

Figure 1 provides an overview of PeerRush, which we discuss in detail in Section 2. The first step involves the identifications of P2P hosts within the monitored network. Then, the P2P traffic categorization module analyzes the network traffic generated by these hosts, and attempts to attribute it to a given P2P application by matching an *application profile* previously learned from samples of traffic generated by known P2P applications. If the P2P traffic does not match any of the available profiles, the traffic is classified as belonging to an "unknown" P2P application (e.g., this may represent a new P2P application release or a previously unknown P2P botnet), and should be further analyzed by the network administrator. On the other hand, if the P2P traffic matches more than one profile, an auxiliary *disambiguation* module is used to "break the tie", and the traffic is labeled as belonging to the closest P2P application profile.

The application profiles can model the traffic characteristics of legitimate P2P applications as well as different P2P-botnets. It is common for security researchers to run botnet samples in a controlled environment to study their system and network activities [3]. The traffic collected during this process can then be used as a sample for training a specific P2P-botnet application profile, which can be plugged into our P2P traffic categorization module. In summary this paper makes the following contributions:

- We present PeerRush, a system for **P2P traffic categorization** that enables the accurate identification of *unwanted* P2P traffic, **including encrypted P2P traffic and different types of P2P botnet traffic**. To achieve these goals, we engineer a set of novel statistical features and classification approaches that provide both accuracy and robustness to noise.
- We collected a variety of P2P traffic datasets comprising of P2P traffic generated by five different legitimate P2P applications used in different configura-

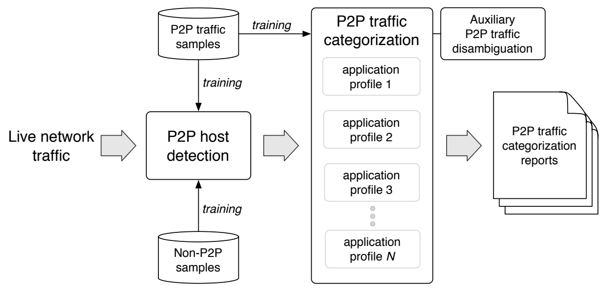


Fig. 1. PeerRush system overview.

tions, and three different P2P botnets including a P2P botnet that employs encrypted P2P traffic. We are making these datasets *publicly available*.
– We performed an extensive evaluation of PeerRush's classification accuracy and noise resistance. Our results show that we can detect all the considered types of P2P traffic with up to 99.5% true positives and 0.1% false positives. Furthermore, PeerRush can correctly categorize the P2P traffic of a specific P2P application with a misclassification rate of 0.68% or less.

2 System Overview

PeerRush's main goal is to enable the discovery of *unwanted* P2P traffic in a monitored computer network. Because the exact definition of what traffic is unwanted depends on the management and security policies of each network, we take a generic P2P traffic categorization approach, and leave the final decision on what traffic is in violation of the policies to the network administrator.

To achieve accurate P2P traffic categorization, PeerRush implements a two-stage classification system that consists of a *P2P host detection* module, and a *P2P traffic categorization* module, as shown in Figure 1. PeerRush partitions the stream of *live* network traffic into time windows of constant size W (e.g., $W = 10$ minutes). At the end of each time window, PeerRush extracts a number of statistical features from the observed network traffic, and translates the traffic generated by each host H in the network into a separate feature vector F_H (see Section 2.1 for details). Each feature vector F_H can then be fed to a previously trained statistical classifier that specializes in detecting whether H may be running a P2P application, as indicated by its traffic features within the considered time window. Splitting the traffic analysis in time windows allows to generate periodic reports and leads to more accurate results by aggregating outputs obtained in consecutive time windows (see Section 3.3).

The classifier used in the *P2P host detection* is trained using samples of network traffic generated by hosts that are known to be running a variety of P2P applications, as well as samples of traffic from hosts that are believed not to be running any known P2P application (see Section 3.1). Once a host H is classified as a *P2P host* within a given time window W by the first module, its current network traffic (i.e., the traffic collected during the current analysis time window W) is sent to the *P2P traffic categorization* module. This module consists of a number of *one-class classifiers* [20], referred to as "application profiles" in Figure 1, whereby each classifier specializes in detecting whether H may be running a specific P2P application or not. Each one-class classifier is trained using only previously collected traffic samples related to a known P2P application. For example, we train a one-class classifier to detect Skype traffic, one for eMule, one for the P2P-botnet Storm, and etc. This allows us to build a new application profile independently from previously learned traffic models. Therefore, we can train and deploy a different optimal classifier configuration for each target P2P application and analysis time window W.

Given the traffic from H, we first translate it into a vector of categorization features, or *traffic profile*, P_H (notice that these features are different from the detection features F_H used in the previous module). Then, we feed P_H to each of the available one-class classifiers, and each classifier outputs a score that indicates how close the profile P_H is to the application profile that the classifier is trained to recognize. For example, if the Skype one-class classifier outputs a high score, this means that P_H closely resembles the P2P traffic generated by Skype. If none of the one-class classifiers outputs a high enough score for P_H, PeerRush cannot attribute the P2P traffic of H to a known P2P application, and the P2P traffic profile P_H is labeled as "unknown". This decision may be due to different reasons. For example, the detected P2P host may be running a new P2P application for which no traffic sample was available during the training of the application profiles, or may be infected with a previously unknown P2P-botnet.

Because of the nature of statistical classifiers, while a host H is running a single P2P application more than one classifier may declare that P_H is close to their application profile. In other words, it is possible that the *P2P traffic categorization* module may conclude that H is running either Skype or eMule, for example. In these cases, to try to break the tie PeerRush sends the profile P_H to a disambiguation module, which consists of a multi-class classifier that specializes in deciding what application profile is actually the closest to an input profile P_H. Essentially, the output of the disambiguation module can be used by the network administrator in combination with the output of the single application profiles that "matched" the traffic to help in further investigating and deciding if the host is in violation of the policies.

In the following, we detail the internals of the P2P traffic detection and categorization modules. It is worth noting that while some of the ideas we use for the detection module are borrowed from previous work on P2P traffic detection (e.g., [23]) and are blended into our own P2P host detection approach, **the design and evaluation of the P2P traffic categorization component include many novel P2P traffic categorization features and traffic classification approaches**, which constitute our main contributions.

2.1 P2P Host Detection

Due to the nature of P2P networks, the traffic generated by hosts engaged in P2P communications shows distinct characteristics, which can be harnessed for detection purposes. For example, *peer churn* is an always-present attribute of P2P networks [18], causing P2P hosts to generate a noticeably high number of failed connections. Also, P2P applications typically discover and contact the IP address of other peers without leveraging DNS queries [21]. Furthermore, the peer IPs are usually scattered across many different networks. This makes P2P traffic noticeably different from most other types of Internet traffic (e.g, web browsing traffic). To capture the characteristics of P2P traffic and enable P2P host detection, PeerRush measures a number of statistical features extracted from a *traffic time window*. First, given the traffic observed during a time window of length W (e.g., 10 minutes), the network packets are aggregated into flows, where each flow is identified by a 5-tuple (`protocol`, `srcip`, `srcport`, `dstip`, `dstport`). Then, to extract the features related to a host H, we consider all flows whose `srcip` is equal to the IP address of H, and compute a vector F_H that includes the following features:

Failed Connections: we measure the number of failed TCP and (virtual) UDP connections. Specifically, we consider as *failed* all TCP or UDP flows for which we observed an outgoing packet but no response, and all TCP flows that had a reset packet. We use two versions of this feature: (1) the number of failed connections as described above, and (2) the number of failed connections *per host*, where the failed connections to a same destination host are counted as one.

Non-DNS Connections: we consider the flows for which the destination IP address `dstip` was not resolved from a previous DNS query, and measure two features: (1) the number of non-DNS connections as described above, and (2) non-DNS connections per host, in which all flows to a same destination host are counted as one.

Destination Diversity: given all the `dstip` related to non-DNS connections, for each `dstip` we compute its `/16` IP prefix, and then compute the ratio between the number of distinct `/16` prefixes in which the different `dstips` reside, divided by the total number of distinct `dstips`. This gives us an approximate indication of the *diversity* of the `dstips` contacted by a host H. We consider `/16` IP prefixes because they provide a good approximation of network boundaries. In other words, it is likely that two IP addresses with different `/16` IP prefixes actually reside in different networks owned by different organizations. We compute the destination diversity features for successful, unsuccessful, and all connections.

These three groups of features are designed to accurately pinpoint P2P hosts, since they capture the behavioral patterns of traffic generated by P2P applications. Therefore, the expectation is that the value of these features are higher for P2P hosts in comparison to non-P2P hosts. The time window size W is a configurable parameter. Intuitively, longer time windows allow for computing more accurate values for the features, and consequently yield more accurate results (in Section 3 we experiment with W ranging form 10 to 60 minutes).

To carry out the detection, at the end of each time window we input the computed feature vectors F_H (one vector per host and per time window) to a classifier based on decision trees (see Section 3.2 for details). To train the classifier, we use a dataset of traffic that includes non-P2P traffic collected from our departmental network, as well as the traffic generated by a variety of P2P applications, including Skype, eMule, BitTorrent, etc., over several days. The data collection approach we used to prepare the training datasets and assess the accuracy of the P2P host detection module is discussed in detail in Section 3.1.

2.2 P2P Traffic Categorization

After we have identified P2P hosts in the monitored network, the P2P traffic categorization module aims to determine what type of P2P application these hosts are running. Since different P2P applications (including P2P-botnets) use different P2P protocols and networks (i.e., they connect to different sets of peers), they show distinguishable behaviors in terms of their network communication patterns. Therefore, we construct a classification system that is able to learn different P2P application profiles from past traffic samples, and that can accurately categorize new P2P traffic instances.

As shown in Figure 1, the categorization module consists of a number of *one-class classifiers* [20] that specialize in recognizing a specific application profile. For example, we train a one-class classifier to recognize P2P traffic generated by Skype, one that can recognize eMule, etc. Also, we build a number of one-class classifiers that aim to recognize different P2P-botnets, such as Storm, Waledac, and a P2P-based version of Zeus. Overall, in our experiments we build eight different one-class classifiers, with five models dedicated to recognizing five different legitimate P2P applications, and three models dedicated to categorizing different P2P-botnets (see Section 3.3). PeerRush can be easily extended to new P2P applications by training a specialized one-class classifier on the new P2P traffic, and plugging the obtained application profile into the categorization module.

Given the traffic generated by a previously detected P2P host H, we first extract a number of statistical features (described below) that constitute the traffic profile P_H of H within a given time window. Then, we feed P_H to each of the previously trained one-class classifiers, and for each of them we obtain a detection score. For example, let s_k be the score output by the classifier dedicated to recognizing Skype. If s_k is greater than a predefined threshold θ_k, which is automatically learned during training, there is a high likelihood that H is running Skype. If no classifier outputs a score s_i (where the subscript i indicates the i-th classifier) greater than the respective application detection threshold θ_i, we label the P2P traffic from H as "unknown". That is, PeerRush detected the fact that H is running a P2P application, but the traffic profile does not fit any of the previously trained models. This may happen in particular if H is running a new P2P applications or an unknown P2P-botnet for which we could not capture any traffic samples to learn its application profile (other possible scenarios are discussed in Section 4).

Notice that the threshold θ_i is set during the training phase to cap the false positive rate to $\leq 1\%$. Specifically, the false positives produced by the i-th classifier over the traffic from P2P applications other than the one targeted by the classifier is $\leq 1\%$. due to the nature of statistical classifiers, it is possible that more than one one-class classifier may output a score s_i greater than the respective detection threshold θ_i, thus declaring that P_H matches their application profile. In this case, to break the tie we use a *P2P traffic disambiguation* module that consists of a multi-class classifier trained to distinguish among the eight different P2P applications that we consider in our experiments. In this case, the multi-class classifier will definitely assign one application among the available ones, and the output of the multi-class classifier can then be interpreted as the most likely P2P application that is running on H. This information, along with the output of each one-class classifier, can then be used by the network administrator to help decide if H violates the network security policies.

The main reason for building the application profiles using one-class classifiers, rather than directly using multi-class classification algorithms, is that they enable a modular classification approach. For example, given a new P2P application and some related traffic samples, we can separately train a new one-class classifier even with very few or no counterexamples (i.e., traffic samples from other P2P applications), and we can then directly plug it into the P2P traffic categorization module. Learning with few or no counterexamples cannot be easily done with multi-class classifiers. In addition, differently from multi-class classifiers, which will definitely assign exactly one class label among the possible classes, by using one-class classifiers we can more intuitively arrive to the conclusion that a given traffic profile P_H does not really match any previously learned P2P traffic and should therefore be considered as belonging to an "unknown" P2P application, for example.

Feature Engineering To distinguish between different P2P applications, we focus on their *management* (or control) traffic, namely network traffic dedicated to maintaining updated information about the overlay P2P network at each peer node [1]. The reason for focusing on management flows and discarding data-transfer flows is that management flows mainly depend on the P2P protocol design and the P2P application itself, whereas data flows are more user-dependent, because they are typically driven by the P2P application user's actions. Because the usage patterns of a P2P application may vary greatly from user to user, focusing on management flows allows for a more generic, user-independent P2P categorization approach. These observations apply to both legitimate P2P applications and P2P-botnets.

Management flows consist of management packets, such as keep-alive messages, periodically exchanged by the peers to maintain an accurate view of the P2P network to which they belong. In a way, the characteristics of management flows serve as a fingerprint for a given P2P protocol, and can be used to build accurate application profiles. The first question, therefore, is how to identify management flows and separate them from the data flows. The answer to this question is complicated by the fact that management packets may be exchanged over management flows that are separate from the data flows, or may be embedded within the data flows themselves, depending on the specific P2P protocol specifications. Instead of making strong assumptions about how managements packets are exchanged, we aim to detect management flows by applying a few intuitive heuristics as described below.

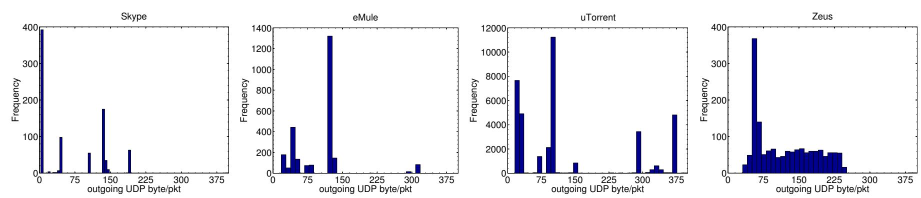
We consider the outgoing flows of each P2P hosts (as detected by the P2P host detection module), and we use the following filters to identify the management packets and discard any other type of traffic:

1) *Inter-packet delays*: given a flow, we only consider packets that have at least a time gap $\delta > \theta_\delta$ between their previous and following packets, where θ_δ is a predefined threshold (set to one second, in our experiments). More precisely, let p_i be the packet under consideration within a flow f, and p_{i-1} and p_{i+1} be the packets in f that immediately precede and follow p_i, respectively. Also, let δ^- and δ^+ be the inter-packet delay (IPD) between p_{i-1} and p_i and between p_i and p_{i+1}, respectively. We label p_i as a management packet if both δ^- and δ^+ are greater than θ_δ. The intuition behind this heuristic is that management packets are exchanged periodically, while data packets are typically sent back-to-back. Therefore, the IPDs of data packets are typically very small, and therefore data packets will be discarded. On the other hand, management packets are typically characterized by much larger IPDs (in fact, a $\theta_\delta = 1s$ IPD is quite conservative, because the IPDs between management packets are often much larger).
2) *Duration of the connection*: P2P applications often open long-lived connections through which they exchange management packets, instead of exchanging each management message in a new connection (notice that UDP packets that share the same source and destinations IPs and ports are considered as belonging to the same virtual UDP connection). Therefore, we only consider flows that appear as *long-lived* relative to the size W of the traffic analysis time windows, and we discard all other flows. Specifically, flows that are shorter than $\frac{W}{3}$ are effectively excluded from further analysis.
3) *Bi-directionality*: this filter simply considers bi-directional flows only. The assumption here is that management messages are exchanged both ways between two hosts, and for a given management message (e.g., keep-alive) we will typically see a response or acknowledgment.

Notice that these rules are only applied to connections whose destination IP address did not resolve from DNS queries. This allows us to focus only the network traffic that has a higher chance of being related to the P2P application running on the identified P2P host. While a few non-P2P flows may still survive this prefiltering (i.e., flows whose destination IP was not resolved from DNS queries, and that are related to some non-P2P application running on the same P2P host), thus potentially constituting noise w.r.t. the feature extraction process, they will be excluded (with very high probability) by the management flow identification rules outlined above.

After we have identified the management (or control) flows and packets, we extract a number of features that summarize the "management behavior" of a P2P host. We consider two groups of features: features based on the distribution of bytes-per-packet (BPP) in the management flows, and feature based on the distribution of the inter-packet delays (IPD) between the management packets. Specifically, given a P2P host and its P2P management flows, we measure eight features computed based on the distribution of BPPs of all incoming and outgoing TCP and UDP flows and the distribution of IPDs for all incoming and outgoing TCP and UDP packets within each management flow.

The intuition behind these features is that different P2P applications and protocols use different formats for the management messages (e.g., keep-alive), and therefore the distribution of BPP will tend to be different. Similarly, different P2P applications typically behave differently in terms of the timing between when management messages are exchanged between peers. As an example, Figure 2 reports the distribution of BPP for four different P2P applications. As can be seen from the figure, different applications have different *profiles*, which we leverage to perform P2P traffic *categorization*.



(a) Skype (b) eMule (c) μTorrent (d) Zeus

Fig. 2. Distribution of bytes per packets for management flows of different P2P apps.

To translate the distribution of the features discussed above into a pattern vector, which is a more suitable input for statistical classifiers, we proceed as follows. First, given a host H and its set of management flows, we build a histogram for each of the eight features. Then, given a histogram, we sort its "peaks" according to their height in descending order and select the top ten peaks (i.e., the highest ten). This is done to isolate possible noise in the distribution, and to focus only on the most distinguishing patterns. For each of these peaks we record two values: the location (in the original histogram) of the peak on the x axis, and its relative height compared to the remaining top ten peaks. For example, the relative height $\hat{h}_k$ of the k-th peak is computed as $\hat{h}_k = h_k / \sum_{j=1}^{10} h_j$, where h_j is the height of the j-th peak. This gives us a vector of twenty values for each feature. So the overall feature vector contains 160 features.

This format of the feature vectors is used both as input to the application-specific one-class classifiers and the P2P traffic disambiguation multi-class classifier (see Figure 1). The learning and classification algorithms with which we experimented and the datasets used for training the P2P traffic categorization module are discussed in Section 3.3.

3 Evaluation

3.1 Data Collection

PeerRush relies on three main datasets for the training of the P2P host detection and traffic categorization modules: a dataset of P2P traffic generated by a variety of P2P applications, a dataset of traffic from three modern P2P botnets, and a dataset of non-P2P traffic. In the next Sections, we will refer back to these datasets when presenting our evaluation results, which include cross-validation experiments. We plan to make our P2P traffic datasets openly available to facilitate further research and to make our results easier to reproduce[3].

(D1) Ordinary P2P Traffic To collect the P2P traffic dataset, we built an experimental network in our lab consisting of 11 distinct hosts which we used to run 5 different popular P2P applications for several weeks. Specifically, we dedicated 9 hosts to running Skype, and the two remaining hosts to run, at different times, eMule, μTorrent, Frostwire, and Vuze. This choice of P2P applications provided diversity in both P2P protocols and networks (see Table 1). The 9 hosts dedicated to Skype were divided into two groups: we configured two hosts with high-end hardware, public IP addresses, and no firewall filtering. This was done so that these hosts had a chance to be elected as Skype super-nodes (indeed, a manual analysis of the volume of traffic generated by these machines gives us reasons to believe that one of the two was actually elected to become a super-node). The remaining 7 hosts were configured using filtered IP addresses, and resided in distinct sub-networks. Using both filtered and unfiltered hosts allowed us to collect samples of Skype traffic that may be witnessed in different real-world scenarios. For each host, we created one separate Skype account and we made some of these accounts be "friends" with each other and with Skype instances running on machines external to our lab. In addition, using AutoIt (`autoitscript.com/site/autoit`), we created a number of scripts to simulate user activities on the host, including periodic chat messages and phone calls to friends located both inside and outside of our campus network. Overall, we collected 83 days of a variety of Skype traffic, as shown in Table 1.

We used other two distinct unfiltered hosts to run each of the remaining legitimate P2P applications. For example, we first used these two hosts to run two instances of eMule for about 9 consecutive days. During this period, we initiated a variety of file searches and downloads[4]. Whenever possible, we used AutoIt to automate user interactions with the client applications. We replicated this process to collect approximately the same amount of traffic from FrostWire, μTorrent, and Vuze.

(D2) P2P Botnet Traffic In addition to popular P2P applications, we were able to obtain (mainly from third parties) several days of traffic from three different P2P-botnets: Storm [8], Waledac [16], and Zeus [12]. It is worth noting that the Waledac traces were collected before the botnet takedown enacted by Microsoft, while the Zeus traces are from a very recent version of a likely still active Zeus botnet that relies entirely on P2P-based command-and-control (C&C) communications. Table 1 indicates the number of hosts and days of traffic we were able to obtain, along with information about the underlying transport protocol used to carry P2P management traffic.

[3] Please contact the authors to obtain a copy of the datasets.

[4] To avoid potential copyright issues we made sure to never store the downloads permanently.

(D3) Non-P2P Traffic To collect the dataset of non-P2P traffic, we proceeded as follows. We monitored the traffic crossing our departmental network over about 5 days, and collected each packet in an anonymized form. Specifically, we wrote a sniffing tool based on `libpcap` that can anonymize the packets "on the fly" by mapping the department IPs to randomly selected `10.x.x.x` addresses using a keyed hash function, and truncating the packets payloads. We leave all other packet information intact. Also, we do not truncate the payload of DNS response packets, because we need domain name resolution information to extract a number of statistical features (see Section 2). Because users in our departmental network may use Skype or (sporadically) some P2P file-sharing applications, we used a number of conservative heuristics to filter out potential P2P hosts from the non-P2P traffic dataset.

To identify possible Skype nodes within our network, we leverage the fact that whenever a Skype client is started, it will query domain names ending in `skype.com` [7]. Therefore, we use the DNS traffic collected from our department to identify all hosts that query any Skype-related domain names, and we exclude them from the traces. Obviously, this is a very conservative approach, because it may cause a non-negligible number of false positives, excluding nodes that visit the `www.skype.com` website, for example, but that are not running Skype. However, we chose this approach because it is difficult to devise reliable heuristics that can identify with high precision what hosts are running Skype and for how long (that's why systems such as PeerRush needed in the first place), and using a conservative approach gives us confidence on the fact that the non-P2P dataset contains a very low amount of noise. Using this approach, we excluded 14 out of 931 hosts in our network.

To filter out other possible P2P traffic, we used Snort (`snort.org`) with a large set of publicly available P2P detection rules based on payload content inspection. We ran Snort in parallel to our traffic collection tool, and excluded from our dataset all traffic from hosts that triggered a Snort P2P detection rule. Again, we use a very conservative approach of eliminating *all* traffic from suspected P2P hosts to obtain a clean non-P2P dataset. Using this conservative approach, we filtered out 7 out of 931 IP addresses from our network.

The heuristics-based traffic filtering approach discussed above aims to produce a dataset for which we have reliable *ground truth*. While our heuristics are quite conservative, and may erroneously eliminate hosts that are not actually engaging in P2P traffic, we ended up eliminating only a small fraction of hosts within our network. Therefore, we believe the remaining traffic is representative of non-P2P traffic in our department. Naturally, it is also possible that the non-P2P dataset may contain some P2P traffic (e.g., encrypted or botnet traffic) that we were not able to label using Snort or our heuristics, thus potentially inflating the estimated false positives generated by PeerRush. However, since this would in the worst case underestimate the accuracy of our system, not overestimate it, we can still use the dataset for a fair evaluation.

Table 1. P2P traffic dataset summary

Application	Protocol	Hosts	Capture Days	Transport
Skype	Skype	9	83	TCP/UDP
eMule	eDonkey	2	9	TCP/UDP
FrostWire	Gnutella	2	9	TCP/UDP
μTorrent	BitTorrent	2	9	TCP/UDP
Vuze	BitTorrent	2	9	TCP/UDP
Storm	-	13	7	UDP
Zeus	-	1	34	UDP
Waledac	-	3	3	TCP

Table 2. P2P Host Detection: results of 10-fold cross-validation using J48+AdaBoost

time window	TP	FP	AUC
60 min	99.5%	0.1%	1
40 min	99.1%	0.8%	0.999
20 min	98.4%	1.1%	0.999
10 min	97.9%	1.2%	0.997

3.2 Evaluation of P2P Host Detection

Balanced Dataset To evaluate the P2P host detection module, we proceed as follows. We perform cross-validation tests using the datasets **D1**, **D2**, and **D3** described in Section 3.1. We then applied the process described in Section 2.1 to extract statistical features and translate the traffic into feature vectors (one vector per host and per observation time window). Because the volume of Skype-related traffic in **D1** was much larger than the traffic we collected from the remaining popular P2P applications, we under-sampled (at random) the Skype-related traffic to obtain a smaller, balanced dataset. Also, we under-sampled from **D3** to obtain approximately the same number of labeled instances derived from P2P and non-P2P traffic. Consequently, our training set for this module contains roughly the same number of samples from legitimate P2P applications and from the non-P2P traffic.

Cross-validation To perform cross-validation, we initially excluded **D2**, and only considered a balanced version of **D1** and **D3**. As a classifier for the P2P host detection module we used *boosted decision trees*. Specifically, we employ Weka to run 10-fold cross-validation using the J48 decision tree and the AdaBoost meta-classifier (we set AdaBoost to combine 50 decision trees). We repeated the same experiment by measuring the features for different values for the time window length W ranging from 10 to 60 minutes. Due to space constraints, we only discuss the results for the shortest and longest time windows. For $W = 60$ minutes, we had 1,885 P2P and 3,779 non-P2P training instances, while for 10 minutes we had 10,856 P2P and 19,437 non-P2P instances. The results in terms of true positive rate (TP), false positive rate (FP), and area under the ROC curve (AUC) are summarized in Table 2. As can be seen, the best results are obtained for the 60 minutes time window, with a 99.5% true positives and a 0.1% false positives. This was expected, because the more time we wait, the more evidence we can collect on whether a host is engaging in P2P communications. However, even at a 10 minutes time window, the classifier perform fairly well, with a true positive rate close to 98%, a false positive rate of 1.2%, and an AUC of 99.7%.

Botnets Besides cross-validation, we performed two additional sets of experiments. First, we train the P2P host detection classifier (we use J48+AdaBoost) using **D1** and **D3**, but not **D2**. Then, given the obtained trained classifier, we test against the P2P botnet traffic **D2**. The results of this experiments are summarized in Table 3 (due to space constraints we only show results for $W = 10$

Table 3. P2P Host Detection: classification of P2P botnet traffic instances

Time Win.	Botnet	Instances	TPs	IPs detected
60 min	Storm	306	100%	13 out of 13
	Zeus	825	92.48%	1 out 1
	Waledac	75	100%	3 out 3
10 min	Storm	1,834	100%	13 out of 13
	Zeus	4,877	33.46%	1 out of 1
	Waledac	444	100%	3 out of 3

Table 4. P2P Host Detection: "leave one application out" test

time window: 10 minutes			
Left out app.	**Test on left out app.**		
	Instances	**TPs**	**IPs detected**
Skype	99,165	90.26%	9 out of 9
eMule	2,316	100%	2 out of 2
Frostwire	2,316	100%	2 out of 2
μTorrent	2,035	100%	2 out of 2
Vuze	2,035	100%	2 out of 2

and $W = 60$). As we can see, the P2P host detection classifier can perfectly classify all the instances of Storm and Waledac traffic. Zeus traffic is somewhat harder to detect, although when we set the time window for feature extraction to 40 minutes or higher we can correctly classify more than 90% of all Zeus traffic instances. We believe this is due to the fact that in our Zeus dataset the host infected by the Zeus botnet sometimes enters a "dormant phase" in which the number of established connections decreases significantly. Also, by considering traffic *over different time windows*, all the IP addresses related to the P2P botnets are correctly classified as P2P hosts. That is, if we consider the Zeus-infected host over a number of consecutive time windows, the Zeus P2P traffic is correctly identified in at least one time window, allowing us to identify the P2P host. Therefore, the 33.46% detection rate using 10-minute time windows is not as low as it may seem, in that the host was labeled as a P2P host at least once in every three time windows.

Leave-one-out In addition, we performed a number of experiments to assess the *generalization ability* of our P2P host classifier. To this end, we again trained the classifier on **D1** and **D3**. This time, though, we train the classifier multiple times, and every time we leave out one specific type of P2P traffic from **D1**. For example, first we train the classifier while leaving out all Skype traffic from the training dataset, and then we test the obtained trained classifier on the Skype traffic that we left out. We repeat this leaving out from **D1** one P2P application at a time (as before, we did not include **D2** in the training dataset). The results of this set of experiments for $W = 10$ are reported in Table 4. The results show that we can detect most of the left out applications perfectly in all time windows. In case of Skype, the classifier can still generalize remarkably well and correctly classifies more than 90% of the Skype instances using $W = 10$. Using larger time windows improves the results further, because the statistical features can be measured more accurately. Also, the *IPs detected* column shows that all IP addresses engaged in P2P communications are correctly classified as P2P hosts.

Other non-P2P instances Besides the cross-validation experiments, to further asses the false positives generated by our system we tested the P2P host detection classifier over the portion of the non-P2P traffic dataset that was left out from training (due to under-sampling). For $W = 60$ minutes we obtained a FP rate of 0.29%. With $W = 10$ minutes, we obtained a FP rate of 1.19%.

3.3 Evaluation of P2P Traffic Categorization

In this Section, we evaluate the P2P traffic categorization module. First, we separately evaluate the one-class classifiers used to learn single application profiles (**E1**) and the auxiliary P2P traffic disambiguation module (**E2**). Then, we evaluate the entire P2P traffic categorization module in a scenario that replicates the intended use of PeerRush after deployment (**E3**).

In all our experiments, we translate a host's traffic into statistical features using the process described in Section 2.2. Similar to the evaluation of the P2P host detection module presented in Section 3.2, we experiment with values of the time windows W ranging from 10 to 60 minutes, although due to space constraints we can only discuss a sub-set of the obtained results.

(E1) P2P Application Profiles As mentioned in Section 2.2, each application profile is modeled using a one-class classifier. Specifically, we experiment with the Parzen, KNN, and Gaussian *data description* classifiers detailed in [20] and implemented in [19]. To build a one-class classifier (i.e., an application profile) for Skype traffic, for example, we use part of the Skype traffic from **D1** as a *target* training dataset, and a subset of non-Skype traffic from the other legitimate P2P applications (again from **D1**) as an *outlier* validation dataset. This validation dataset is used for setting the classifier's detection threshold so to obtain $\leq 1\%$ false positives (i.e., non-Skype traffic instances erroneously classified as Skype). Then we use the remaining portion of the Skype and non-Skype traffic from **D1** that we did not use for training and threshold setting to estimate the FP, TP, and AUC. We repeat the same process for each P2P application in **D1** and P2P botnets in **D2**. Each experiment is run with a 10-fold cross-validation setting for each of the considered one-class classifiers. The results of these experiments are summarized in Table 5. The "#Inst." column shows the overall number of *target* instances available for each traffic class.

Besides experimenting with different one-class classifiers, we also evaluated different combinations of features and different feature transformation algorithms, namely principal component analysis (PCA) and feature scaling (Scal.). The "Configuration" column in Table 5 shows, for each different time window, the best classifier and feature configuration. For example, the first row of results related to Skype reports the following configuration: "60min; KNN; 32 feat.; PCA". This means that the best application profile for Skype when considering a 60 minutes traffic time window was obtained using the KNN algorithm, 32 features (out of all possible 160 features we extract from the traffic characteristics), and by applying the PCA feature transformation. In the remaining rows, "Scal." indicates features scaling, while "-" indicates no feature transformation.

Notice that because we use one-class classifiers, each application profile can be built independently from other profiles. Therefore, we can train and deploy different optimal classifier configurations depending on the target P2P application and desired time window W for traffic analysis. For example, for a time window of 60 minutes, we can use a KNN classifier with 32 features transformed using PCA for Skype, and a Parzen classifier with 16 scaled features for eMule. This gives us a remarkable degree of flexibility in building the application profiles, compared to multi-class classifiers, because in the latter case we would be

Table 5. One-Class Classification Results

App.	#Inst.	Configuration	TP	FP	AUC
Skype	526	60min; KNN; 32 feat.; PCA	96.54%	0.74%	0.998
	579	10min; Parzen; 16 feat.; -	91.27%	1.00%	0.978
eMule	387	60min; Parzen; 16 feat; Scal.	90.64%	0.92%	0.989
	483	10min; KNN; 8 feat.; PCA	88.40%	1.16%	0.961
Frostwire	382	60min; KNN; 12 feat.; PCA	85.58%	0.96%	0.966
	467	10min; KNN; 8 feat.; PCA	92.68%	1.25%	0.989
μTorrent	370	60min; KNN; 8 feat.; -	92.94%	1.30%	0.948
	609	10min; Parzen; 4 feat.; Scal.	94.55%	1.24%	0.992
Vuze	376	60min; KNN; 8 feat.; -	91.92%	0.95%	0.979
	514	10min; KNN; 8 feat.; PCA	84.18%	1.17%	0.964
Storm	162	60min; Parzen; 16 feat.; -	100%	0%	1.000
	391	10min; Parzen; 12 feat.; PCA	100%	0%	1.000
Zeus	375	60min; KNN; 4 feat.; -	97.29%	0.99%	0.996
	188	10min; KNN;12 feat.; -	94.53%	0.79%	0.976
Waledac	37	60min; Gaussian; 12 feat.; PCA	99.99%	0.90%	0.998

limited to using the same algorithm and set of features for all application profiles. Furthermore, using multi-class classifiers makes identifying P2P traffic that does not match any of the profiles (i.e., "unknown" P2P traffic) more straightforward.

Table 5 shows that for most applications we can achieve a TP rate of more than 90% with an FP rate close to or below 1%. In particular, all traffic related to P2P botnets can be accurately categorized with very high true positive rates and low false positives. These results hold in most cases even for time windows of $W = 10$ minutes, with the exception of Waledac, for which we were not able to build a comparably accurate application profile using a 10 minutes time window, since we did not have enough target instances to train a classifier (this unsatisfactory result is omitted from Table 5).

(E2) P2P Traffic Disambiguation When a traffic instance (i.e., the feature vector extracted from the traffic generated by a host within a given time window) is classified as *target* by more than one application profile, we can use the traffic disambiguation module to try to break the tie. The disambiguation module (see Section 2) consists of a multi-class classifier based on the Random Forest algorithm combining 100 decision trees. In this case, we use all 160 features computed as described in Section 2.2 without any feature transformation. We independently tested the disambiguation module using 10-fold cross-validation. On average, we obtained an accuracy of 98.6% for a time window of 60 minutes, 98.3% for 40 minutes, 97.5% for 20 minutes, and 96.7% for 10 minutes.

(E3) Overall Module Evaluation In this section we aim to show how the P2P categorization module performs overall, and how robust it is to noise. To this end, we first split the **D1** dataset into two parts: (i) a training set consisting of 80% of the traffic instances (randomly selected) that we use for training the single application profiles, automatically learn their categorization thresholds, and to train the disambiguation module; (ii) a test set consisting of the remaining 20% of the traffic instances.

To test both the accuracy and robustness of PeerRush's categorization module, we also perform experiments by artificially adding noise to the traffic instances in the test dataset. In doing so, we consider the case in which non-P2P traffic is misclassified by the P2P host detection module and not completely filtered out through the management flow identification process described in

Section 2.2. To obtain noisy traffic we processed the entire **D3** dataset (about 5 days of traffic from 910 distinct source IP addresses) to identify all flows that resemble P2P management flows. To simulate a *worst case scenario*, we took all the noisy management-like flows we could obtain, and we randomly added these flows to *all* the P2P traffic instances in the 20% test dataset described above. Effectively, we simulated the scenario in which the traffic generated by a known P2P host is overlapped with non-P2P traffic from one or more randomly selected hosts from our departmental network.

For each test instance fed to the categorization module, we have the following possible outcomes: (1) the instance is assigned the correct P2P application label; (2) no application profile "matches", and the P2P traffic instance is therefore labeled as "unknown"; (3) more than one profile "matches", and the instance is sent to the disambiguation module. Table 6 and Table 7 report a summary of the obtained results related to the 20% test dataset with and without extra added noise, considering $W = 60$ minutes. For example, Table 7 shows that over 90% of the Skype-related traffic instances can be correctly labeled as being generated by Skype with 1.29% FP, even in the presence of added noise.

Overall, 45 out of 732 (6.15%) of the noisy test traffic instances were classified as "unknown", 32 instances were passed to the disambiguation module and all of them were classified perfectly. Finally, only 5 out of 732 instances were eventually misclassified as belonging to the wrong P2P application. It is worth noting that an administrator could handle the "unknown" and misclassified instances by relying on the categorization results for a given P2P host across more than one time window. For example, a P2P host that is running eMule may be categorized as "unknown" in one given time window, but has a very high chance of being correctly labeled as eMule in subsequent windows, because the true positive rate for eMule traffic is above 93%. In fact, in our experiments, by considering the output of the categorization module over more than one single time window we were always able to attribute the P2P traffic in our test to the correct application.

As we can see by comparing Table 6 and Table 7, the extra noise added to the P2P traffic instances causes a decrease in the accuracy of the P2P traffic categorization module. However, in most cases the degradation is fairly limited. The noise has a more negative impact on the categorization of Storm and Waledac, in particular. Notice, though, that the results reported in Table 7 are again related to single traffic instances (i.e., a single time window). This means that if a Storm- or Waledac-infected host connects to its botnet for longer than one time window, which is most likely the case since malware often makes itself permanent into the compromised systems, the probability of correct categorization would increase. Therefore, even in the scenario in which each P2P host is also running other network applications that may introduce noise in the management flow identification and feature extraction process, we can accurately detect the P2P traffic, and still achieve satisfactory categorization results.

We also wanted to determine how PeerRush's categorization module would deal with noise due to detection errors in the P2P host detection module. To this end, we further tested the classifier using traffic from the non-P2P traffic dataset that were misclassified as P2P by the P2P host detection module. We found that considering a time window of 60 minutes, only 35 traffic instances misclassified by the P2P host detection module passed the management flow discovery filter. Of these, 33 were classified as "unknown" by the categorization module, one was misclassified as both Skype and μTorrent, and one was misclassified as Zeus.

Table 6. 80/20 experiments

time window: 60 minutes			
Application	**TP**	**FP**	**AUC**
Skype	100%	0.86%	1
eMule	93.59%	1.44%	0.9968
Frostwire	88.31%	0.97%	0.9873
μTorrent	96.97%	1%	0.9789
Vuze	93.1%	0.7%	0.9938
Storm	100%	0%	1
Zeus	96.69%	1.26%	0.9964
Waledac	57.14%	0.83%	0.9420

Classified as "unknown": 3.96% (29 out of 732)
Misclassified as other P2P: 0% (0 out of 732)
Disambiguation needed: 4.64% (34 out of 732)
· Correctly disambiguated: 33, Incorrectly disambiguated: 1
Total misclassified as other P2P: 0.14% (1 out of 732)

Table 7. 80/20 with extra noise

time window: 60 minutes			
Application	**TP**	**FP**	**AUC**
Skype	90.4%	1.29%	0.9891
eMule	94.87%	2.39%	0.9935
Frostwire	94.73%	0.48%	0.9927
μTorrent	98.99%	0.66%	0.9997
Vuze	93.22%	3.02%	0.9873
Storm	45.45%	0%	0.7273
Zeus	97.32%	0.72%	0.9991
Waledac	40%	0.8%	0.8610

Classified as "unknown": 6.15% (45 out of 732)
Misclassified as other P2P: 0.68% (5 out of 732)
Disambiguation needed: 4.37% (32 out of 732)
· Correctly disambiguated: 32, Incorrectly disambiguated: 0
Total misclassified as other P2P: 0.68% (5 out of 732)

4 Discussion

PeerRush is intentionally built using a modular approach, which allows for more flexibility. For example, as shown in Section 3, it may be best to use a different number of features and different classification algorithms to learn the traffic profile of different P2P applications. To build the profile for a new P2P application we can apply a model selection process, which is commonly used for other machine learning tasks, to find the best classifier configuration for the job, and then we can plug it directly into PeerRush.

One parameter that has direct influence on all the system modules is the observation time window used to split and translate the network traffic into instances (or feature vectors). It is important to notice that while different modules need to extract different statistical features from the same time window, all features can be extracted incrementally, and each given module can simply use the appropriate subset of all the extracted features for its own classification purposes. Also, while all modules perform quite well in most cases by setting the time window length to 10 minutes, the results tend to improve for larger time windows, because this allows the feature extraction process to *collect more evidence*. Therefore, fixing the observation time window at 60 minutes for all modules may be a good choice. However, this choice depends on the desired trade-off between the *detection time* and the *categorization accuracy*.

It is possible that a host may be running more than one P2P application at the same time (or there may be a NAT device that effectively aggregates multiple single hosts), in which case the traffic patterns of these applications may overlap and prevent a match of the profiles. Therefore, PeerRush may categorize these cases as unknown P2P traffic. However, in many practical cases not all P2P applications will be *active* at the same time. Therefore, the analysis of traffic across different time windows applied by PeerRush may still allow for effectively distinguishing among P2P applications. However, notice that even in the cases when a host continuously runs more than one active P2P application at the same time, the host will be detected as a P2P host, although its P2P traffic may be classified as "unknown" and may therefore require further analysis by the network administrator.

Botnet developers could try to introduce noise (e.g., dummy packets or random padding) into the management flows to alter the distribution of BPP and IPDs. This may cause a "mismatch" with a previously learned application profile for the botnet. In this case, PeerRush would still very likely detect the P2P botnet hosts as running a P2P application, because the features used by the P2P host detection module are intrinsic to P2P traffic in general (see Section 2.1 and the results in Table 4) and are harder to evade. However, the P2P traffic categorization module may classify the P2P botnet traffic as "unknown", thus requiring further analysis to differentiate the botnet traffic from other possible types of P2P traffic. Because P2P botnet hosts may for example engage in sending large volumes of spam emails, be involved in a distributed denial-of-service (DDoS) attack, or download executable binaries to update the botnet software, one possible way to distinguish P2P traffic related to botnets is to monitor for other suspicious network activities originating from the detected P2P hosts [5].

The developer of a new P2P application, including P2P botnets, may attempt to model its P2P traffic following the behavior of other legitimate P2P applications. Because some networks may consider most P2P applications (legitimate or not) as unwanted, the developer may be restricted to mimic a specific type of P2P traffic that is likely to be allowed in most networks (e.g., Skype traffic). However, while possible, morphing the traffic to mimic other protocols may require significant effort [14].

5 Related Work

While P2P traffic *detection* has been a topic of much research, P2P traffic *categorization* has received very little attention. Because of space limitations, we cannot mention all related work here and we therefore refer the reader to a recent survey by Gomes et al. [4]. In the following, we limit our discussion to the most relevant work on P2P traffic categorization, and on P2P botnet detection.

Hu et al. [9] use flow statistics to build traffic behavior profiles for P2P applications. However, [9] does not attempt to separate P2P control and data transfer traffic. Because data transfer patterns are highly dependent on user behavior, the approach proposed [9] may not generalize well to P2P traffic generated by different users. Furthermore, [9] is limited to modeling and categorizing only two benign non-encrypted P2P applications (BitTorrent and PPLive), and does not consider at all malicious P2P applications. Unlike [9], PeerRush categorizes P2P applications based on an analysis of their P2P control traffic, which captures fundamental properties of the P2P protocol in use and is therefore less susceptible to different application usage patterns. Furthermore, we show that PeerRush can accurately categorize many different P2P applications, including encrypted traffic and different modern P2P botnets.

In [6], Haq et al. discuss the importance of detecting and categorizing P2P traffic to improve the accuracy of intrusion detection systems. However, they propose to classify P2P traffic using deep packet inspection, which does not work well in case of encrypted P2P traffic. More recently, a number of studies have addressed the problem of detecting P2P botnets [5, 22, 23]. However, all these works focus on P2P botnet detection, and cannot categorize the detected malicious traffic and attribute them to a specific botnet family. PeerRush is different because it focuses on *detecting and categorizing unwanted P2P traffic* in general, including a large variety of legitimate P2P applications and botnets.

Coskun et al. [2] proposed to discover hosts belonging to a P2P botnet from a *seed* of compromised hosts. Similarly, [15] analyzes communication graphs to identify P2P botnet nodes. These works focus solely on P2P botnets detection.

6 Conclusion

We presented PeerRush, a novel system for the identification of *unwanted* P2P traffic. We showed that PeerRush can accurately *categorize* P2P traffic and attribute it to specific P2P applications, including malicious applications such as P2P botnets. We performed an extensive evaluation of the system over a variety of P2P traffic datasets. Our results show that PeerRush can detect all the considered types of P2P traffic with up to 99.5% true positives and 0.1% false positives. Furthermore, PeerRush can attribute the P2P traffic to a specific P2P application with a misclassification rate of 0.68% or less.

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