Using OpenFlow to Enable Privacy-Preserving P2P Traffic Detection

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Abstract*—Application layer Deep Packet Inspection (DPI) is presently the predominant method to detect and regulate p2p traffic. Even if one chooses to ignore the ethical debate on DPI and privacy, most of the existing solutions rely on traffic and payload signatures/features which are not robust against NATing, client/protocol/port changes, encryption, and obfuscation. In this paper, we propose a flow-level p2p behavior detector which *only* relies on network layer features and still provides better accuracy and speed than existing non-proprietary techniques. We evaluate existing and propose novel discriminating network layer traffic features using information divergence of p2p and non-p2p traffic. These features are leveraged in low-complexity cross-correlation and log-likelihood frameworks deployed on an OpenFlow-compliant network testbed. We show that an OpenFlow controller can easily extract the features used in this work from the switch's fast path. Accuracy of the proposed method is compared with four prominent techniques using encrypted p2p data on our network and 3.4 million unencrypted flows from public backbone data. The proposed method provides significant improvements of up to 25% in detection rate, 30% in false positive rate, and 240 seconds in detection speed. Evaluations on NATed traffic show that the proposed approach's accuracy is unaffected by NATing.

I. Introduction

High market penetration of broadband connectivity in the past few years has catalyzed a fundamental change in users' traffic characteristics with peer-to-peer (p2p) file sharing content comprising 40-70% of today's Internet's traffic [1]. While p2p traffic volume is decreasing [2], p2p content[1] still represents a major traffic share. Therefore, network operators and service providers would like to detect, classify, regulate and charge for this content. Enterprise networks are also inclined to monitor, and at times block, such content to reduce the risk of information leakage. Universities are concerned about file sharing software that are bandwidth hungry and are mostly used to illegally distribute copyrighted content. Legislative, law enforcement, and intelligence agencies are interested in detecting and regulating p2p content to implement governmental traffic policies and to identify points of presence of suspicious network activities.

[1]Throughout this paper, the term 'p2p traffic/hosts' is used for file sharing hosts. We do not attempt to analyze/detect real-time media traffic (e.g., Skype).

Over the last few years, Deep Packet Inspection (DPI) based solutions that analyze each packet up to the application layer payload have matured to provide commercial-grade performance in detecting and regulating p2p traffic at wirespeeds [3]. Simultaneous to the widespread commercial deployments of DPI products [4]–[9], a global debate has ensued on the ethical, legal and privacy aspects of DPI. In particular, DPI's privacy implications have sparked government-level debates and deliberations in North America and the EU [12]–[15]. Interpretations of USA's Federal Wiretap Act of 1968 [35] and UK's recently enacted Digital Economy Act [36] have added further fuel to this controversy.

Even if this debate is ignored in favor of better traffic visibility and management, most of the existing DPI detectors rely on traffic/payload signatures that are not robust against client and protocol changes [16]–[18]. A new school of thought is now emerging which advocates detecting p2p traffic using behavioral features at application and/or transport layers [20]–[25],[28], [29]. Some of these solutions are also defeated in practical network configurations (such as NATing and tunneling) and under payload cloaking (using encryption and/or obfuscation). P2P software are already exploiting these weaknesses to evade detection with many popular clients now supporting dynamic random port number assignment, chunked file transfers, connection reversal, HTTP masquerading, and payload encryption [10], [11].

In view of the above problems with p2p traffic detection at application and transport layers, we argue that a practical p2p traffic detector should rely *only* on network layer features. The main question looming over payload-oblivious, behavioral detection of p2p traffic at the network layer is: Can it meet the accuracy (detection and false positive rates) and speed (detection delay) requirements expected from a real-time p2p detector?

To address the above question, in this paper we propose and evaluate a network layer p2p traffic detector. We first use information-theoretic tools to evaluate a rich set of existing network layer features which have been used for traffic classification by prior studies [37]. We note that most of these existing features do not vary significantly across p2p and non-p2p traffic. We therefore extend the existing feature set by proposing novel features which can characterize p2p traffic more accurately. Existing and novel features are leveraged in low-complexity cross-correlation and log-likelihood frameworks to detect p2p traffic in real-time.

For empirical evaluation of the proposed method, we implement it on an OpenFlow testbed deployed at NUST, Pakistan. For performance benchmarking of the proposed method, we also implement and evaluate four existing p2p detectors on the OpenFlow testbed. NOX implementations of all the algorithms are released publicly[2] to facilitate future research in this area. Traffic used for performance evaluation comprises an encrypted and NATed dataset from NUST's network and 3.4 million flows from a publicly-available, unencrypted backbone dataset.

ROC-based evaluations for host detection shows that the proposed method renders an improvement of 15% in detection rate, 10% in FP rate, and 9.5 minutes over the second-best technique. Similarly, for the detection of p2p connections, improvements of 25% in detection rate, 30% in FP rate, and 4 minutes in detected delay are observed over existing methods. Evaluation on NATed traffic shows that the proposed p2p connection detection approach's accuracy is unaffected by NATing.

Main technical contributions of this paper are as follows:

- Modeling and evaluation of a comprehensive set of distinguishing *network layer* features that differ considerably among p2p and non-p2p traffic classes;
- Quantification of the divergence among these distinguishing features using information divergence measures;
- A fast and efficient detector that uses 6 network layer features to detect p2p hosts with a detection rate of 97.84%, a false positive rate of 4.01%, and a detection delay of 30 seconds on our evaluation datasets;
- A fast and efficient detector that uses 12 network layer features to detect p2p connections with a true positive rate of 93.27% and a false positive rate of 5.57% using only 8 minutes of traffic in our evaluation datasets;
- An OpenFlow controller application which can easily extract the network features used in this work from the switch's fast path;
- OpenFlow implementation of a suite of p2p detectors which has also been released in open-source to facilitate future performance benchmarking; and
- Collection of an encrypted p2p traffic dataset that has been released publicly [3] to facilitate future research.

Other important contributions of this paper are philosophical in nature:

- Contrary to common intuition which suggests that network layer features should be insufficient for accurate p2p traffic detection, we propose a network layer detector which is accurate, fast, and robust against evasion, and easily outperforms existing application and transport layer detectors on all of these evaluation metrics.
- We show that privacy-preserving, payload-oblivious p2p traffic detection is indeed possible. In fact, such detectors offer a pragmatic middle ground for the two extreme schools of thought on DPI-based traffic classification.

[2]NOX implementations can be downloaded from http://wisnet.nust.seecs.edu.pk/downloads/.

[3]http://wisnet.seecs.nust.edu.pk/projects/ENS/DataSets.html

II. Datasets and Testbed

III. OpenFlow Testbed in NOX

We have deployed the proposed p2p traffic regulator in NUST's campus network using OpenFlow [38] complaint hardware. OpenFlow is an emerging standard for Software Defined Networking (SDN) which separates the control and data plane of a traffic switching device. Similar to contemporary devices, control plane packet switching in OpenFlow is performed using the switch's forwarding tables. However, some traffic can also be forwarded to a software-based controller using the OpenFlow protocol. After its processing, the controller writes flow table entries into the switch using the same protocol.

For all our performance evaluations, we implement p2p detectors on the open-source NOX controller [39] running on a quad-core Intel server. On the switch side, we are using Marvell's xCAT switching platform which is currently deployed in two research labs and one distribution point at NUST. These switches are complaint with the OpenFlow 1.0 specification and support all the required actions in the draft specification. Packets from our p2p datasets are replayed on the network using the `TCPReplay` tool.

The first few packets of each flow are forwarded to the NOX controller to derive the proposed traffic features and perform p2p detection operations. Hard drop actions are set in the switch's flow table for hosts suspected of p2p activity.

A. Datasets

For this study, we use a publicly-available 100 Mbps Ethernet backbone dataset. Since all prominent p2p clients and protocols now support encryption to evade DPI-based p2p regulators, in addition to using this dataset, we independently collected a dataset with labeled encrypted/obfuscated p2p traffic. We have made our dataset publicly available for repeatable performance benchmarking by future studies. In this section, we provide details of the datasets used in this paper.

1) Unencrypted P2P Traffic Dataset: For unbiased performance evaluation, we use the publicly-available WIDE trace data [24]. WIDE trace data was captured at a 100 Mbps Ethernet US-Japan Trans-Pacific backbone link that carries commodity traffic for WIDE member organizations. The WIDE trace was captured from 22:45 March 03, 2006 to 23:40 March 03, 2006. In 55 minutes of packet capturing,

Table I
DURATION OF DATA COLLECTION INTERVALS

From	To	NAT
Oct 20, 2008 06:46	Oct 25, 2008 05:22	No
Oct 29, 2008 06:29	Nov 09, 2008 17:42	No
Nov 10, 2008 08:36	Nov 21, 2008 01:17	No
Jan 24, 2009 13:42	Jan 26, 2009 17:52	Yes
Jan 27, 2009 15:51	Jan 28, 2009 12:11	Yes

Table II
P2P APPLICATIONS' TRAFFIC STATISTICS

Client	Sessions Estb.	Traffic Vol.	Encryption
Vuze 4.0	20	685 MB	RC4
Flashget 1.9.6	62	60.7 MB	Protocol Encryption (Algorithm Unknown)
μTorrent 1.8.1	30	1.08 GB	Forced Encryption (Algorithm Unknown)
BitTorrent 6.1.2	40	1.59 GB	Forced Encryption (Algorithm Unknown)
Deluge 1.0.7	30	171 MB	Forced Entire Stream Encryption (Algorithm Unknown)
BitComet 1.07	20	57.4 MB	Forced Encryption (Algorithm Unknown)
alite 0.3.1	9	413 MB	RC4
eMule v0.49b	203	2.67 GB	Forced Encryption (Algorithm Unknown)

32 million packets totaling over 14 Gigabytes were recorded. Due to privacy concerns, only the first 40-bytes of payload for each packet are available. The trace contains about 3.4 million flows. The WIDE trace is not labeled. To establish ground truth for WIDE trace, we use Karagiannis et al.'s payload classifier [18] and OpenDPI [19]. We note that these payload based classifiers might not be able to identify encrypted traffic; therefore, we only use them to identify unencrypted p2p traffic. Details of these payload classifiers are provided in Section IV-A.

2) Encrypted and NATed P2P Traffic Dataset: We collect traffic traces at the edge router of our university's network. The traffic is generated and consumed by teaching blocks, research labs and administration blocks. Traffic capturing was carried out in five intervals as shown in Table I. In collection intervals 4 and 5, traffic was collected after a Network Address Translation (NAT) server. The goal was to observe the behavior of the detectors when transport and network layer features are masked by a NAT server. The total traffic captured in this dataset was over 170 GB.

In our dataset, the p2p traffic belongs to the BitTorrent, eDonkey and Kademlia protocols. These protocols were chosen as a representative set because they generate the largest volume of p2p traffic on the Internet [1]. During our trace collections for the BitTorrent protocol, we used multiple torrent files for transferring data from/to multiple geographical locations for each torrent session. Multiple torrent clients were used to introduce real-world diversity in the dataset as different clients have different behaviors. For instance, BitTorrent, μTorrent, Vuze, Halite, and Deluge used TCP for communication with a tracker, while BitComet and Flashget used UDP. Other protocol fields and packet sizes also varied from client to client. Encryption was enabled for all the torrent sessions. For eMule sessions, we enabled protocol obfuscation using the "Allow obfuscated connections only" option in the client to ensure logging of encrypted traffic only. Statistics of the p2p file sharing applications' traffic are given in Table II.

The non-p2p traffic contains other traffic classes including HTTP, FTP, streaming video, instant messenger, and Skype. The non-p2p trace data also includes encrypted traffic like https, ssh, gtalk, etc. The average throughput of the non-p2p trace data is 0.6 Mbps. Majority of the non-p2p data uses TCP at the transport layer.

Equipped with these datasets, in the following section we discuss the related work and evaluate existing signature-based approaches on our encrypted dataset.

IV. RELATED WORK AND EVALUATION OF SIGNATURE-BASED APPROACHES

In this section we discuss relevant application, transport and network layer approaches for p2p traffic detection. We also evaluate existing application layer signature-based approaches on unencrypted and encrypted datasets to show that p2p traffic can use encryption to evade such detectors.

A. Related Work

Various application [4]–[9],[16]–[18], transport [20]–[25],[28], [29] and network layer [26], [30] approaches have been proposed to detect p2p traffic. To maintain a logical flow of thought, we defer discussion on signature based approaches to subsequent section and only discuss transport and network layer approaches in this section.

In a seminal work, Karagiannis et al. [20] perform non-payload based detection of p2p traffic using transport protocol (TCP and UDP) and connection patterns of <IP, Port> pairs. Karagiannis et al. extend their work in [21] and used a multilevel approach to design BLINC which uses social, functional, and application level heuristics to detect 80%-90% of p2p traffic with more than 95% accuracy. Collins et al. [23] distinguish between p2p and non-p2p flows using: 1) packet size; 2) amount of data exchanged between hosts; and 3) rate of failed connections. Constantinou and Mavrommatis [22] detect p2p traffic based on the number of peers in a connected group and connection direction. Bartlett et al. [28] detect p2p traffic based on peer coordination and failed connections, bi-directional connections and use of unprivileged ports. In [27], authors use six flow- and protocol-level features to identify p2p traffic.

While many techniques have been proposed to detect p2p traffic at transport layer, network layer detection of p2p traffic has been largely unexplored. Ngiwlay et al. [26] propose to use connected IPs, active transfers, bi-directional active transfers, and IP-relation changes to detect 90% of torrent peers within 10 minutes. Raahemi et al. [30] propose

Table III
EVALUATION OF SIGNATURE-BASED APPROACHES (KPC = KARAGIANNIS' PAYLOAD CLASSIFIER [18]; NON-P2P = UNKNOWN TRAFFIC)

	Unencrypted Trace		Encrypted Trace			
	OpenDPI	KPC	OpenDPI		KPC	
	P2P	P2P	P2P	Non-P2P	P2P	Non-P2P
eMule	100%	100%	0%	100%	39.5%	60.5%
μTorrent	100%	100%	0%	100%	0%	100%
BitTorrent	100%	100%	3.8%	96.2%	5%	95%
Others	100%	100%	0%	100%	64.7%	35.3%

to use protocol, TTL value, IP protocol, IP address and packet length for p2p connection detection. It should be noted that both of these techniques have been designed for and evaluated on BitTorrent's p2p traffic.

We now discuss and evaluate contemporary signature-based approaches for p2p traffic detection. Transport and network layer approaches are evaluated in a later section (Section VI).

B. Signature-based Approaches and their Evaluation

Signature-based DPI traffic classification is a well-known and conventional approach to detect p2p traffic. The main complication with this approach is that it requires a priori knowledge of signatures, protocol interactions and packet formats. However, many of the p2p protocols do not make their documentation publicly available and most of the applications which implement the protocols do not follow the standard specifications. Nevertheless, reasonably robust signatures have been identified by existing studies [16]–[19].

Karagiannis et al. [18] showed the complications in signature-based traffic detection on an OC-48 link. Sen et al. [16] developed signatures for a number of p2p protocols using pattern matching. In [17], heuristics to detect unknown applications are used in conjunction with application signatures to improve detection accuracy. Kim et al. [24] added new signatures to Karagiannis's payload classifier. This signature based detector was also used in an evaluation study [24] to establish the groundtruth for a dataset. We evaluate OpenDPI[4] and Karagiannis et al.'s payload classifier with updated signatures on the encrypted traces that we collected to determine the sensitivity of signature-based schemes to encryption and obfuscation in p2p traffic. Before presenting the evaluation results, we provide a brief description of these approaches.

OpenDPI can efficiently detect over 90 protocols/ applications [19]. The signature-based technique of Karagiannis et al. [18] is able to detect 38 popular p2p applications and 21 non-p2p protocols. In addition to signatures, the method of [18] used three heuristics to address the limitations of the available traces (e.g., some of the traces in [24] only had 16 bytes of payload data). Due to these limitations, the detector could not accurately tell whether "HTTP/1.1 503 Ser, HTTP/1.0 503 Ser and HTTP/1.1 206 Par" were p2p traffic or Web traffic. To resolve this, it was assumed that the traffic belongs to the p2p class whenever the flow is from/to source port, destination port is greater than 1000, and both ports are neither 8000 nor 8080. Similarly, if the source IP or the destination IP matched a suspected p2p source/destination host and the source and destination ports were greater than 500, the traffic was flagged as p2p.

The evaluation results of signature-based approaches on encrypted and non-encrypted p2p traffic are shown in Table III. These results show that while signature based approaches are able to detect unencrypted traffic with 100% accuracy, they are unable to detect majority of the encrypted traffic. OpenDPI is unable to detect any p2p traffic, except 3.8% traffic from a BitTorrent client. After analyzing the traces for those identified connections, we found that all of the identified connections belonged to the NATed trace data and none of the non-NATed BitTorrent connections were identified by OpenDPI. Similarly, Karagiannis' Payload Classifier is unable to detect most of the p2p traffic, except for 5% of NATed BitTorrent connections which were detected using signature matching.

The low detection rates of signature-based approaches show that, despite their privacy invading nature, these classifiers cannot detect p2p traffic if the payload information is cloaked using encryption. To address this shortcoming, in the following section we identify discriminating network layer features that can be used for privacy-preserving p2p traffic detection.

V. IDENTIFICATION OF DISTINGUISHING FEATURES

Preliminary empirical results of the last section reveal the inability of signature based approaches to detect encrypted p2p traffic. We now proceed to design an approach which is resilient to the obfuscation techniques employed by p2p applications. To this end, we subdivide the present problem of p2p hosts and traffic detection into two sub-problems: *identification of discriminating network layer traffic* and *detection using the identified features*. This section focuses on the first problem where we compare traffic generated by p2p hosts/connections and non-p2p hosts/connections to identify distinguishing or divergent features. We note that p2p host detection problem is a simplified version of the p2p traffic detection problem. Nevertheless, in many scenarios it is important to detect p2p hosts; for instance, network operators and service providers might want to charge p2p hosts differently. Therefore, we treat p2p host detection as a separate problem. In this context, we first evaluate a rich set of existing features that have been proposed for traffic classification by prior studies. Subsequently, we propose a new set of discriminant features that can be used to enhance the accuracy of p2p traffic detection.

[4]OpenDPI is the open source version of ipoque's industry leading DPI engine [3].

A. Feature Identification Measure

P2p traffic is fundamentally different from non-p2p traffic because of its distributed design, heterogeneity, connection establishment using peer selection algorithms, and connection shuffling [34]. Hence, it can be intuitively deduced that some features of p2p and non-p2p traffic should diverge significantly. However, judicious selection of the best features that facilitate detection requires a mathematical measure that can quantify the divergence of a feature across p2p and non-p2p traffic. To this end, we model traffic features as discrete random variables by mapping each possible value of a feature to an integer outcome. In case of continuous valued features, we divide the feature space into equal-sized bins and assign an integer value to each bin. For each feature random variable, we compute two histograms using the p2p and non-p2p traces, respectively. By normalizing these histograms, we obtain the Probability Mass Functions (PMFs) of the traffic feature random variables.

To quantify the difference between the PMFs derived from p2p and non-p2p traffic, we first employed the Kullback-Leibler (K-L) information divergence measure [31]. For two PMFs p and q of a discrete random variable X, K-L quantifies the difference between the two PMFs as [31]:

$$D(p\|q) = \sum_{i \in \Lambda} p(i) \log_2 \frac{p(i)}{q(i)}, \tag{1}$$

where Λ is the image of X, and $p(i)$ and $q(i)$ respectively represent the probability of feature value i in p and q.

While the K-L measure provided satisfactory divergence quantification for most traffic features, we encountered three limitations: a) non-symmetry, $D(p\|q) \neq D(q\|p)$, b) lack of normalization, and c) $D(p\|q) = \infty$, if $p(i) \neq 0, q(i) = 0$ for any $i \in \Lambda$. To circumvent these limitations, we resorted to using a mutual information based measure.

Mutual information between two discrete random variables X and Y is defined as:

$$I(X,Y) = \sum_{(i,j) \in \Lambda^{(2)}} f(i,j) \log_2 \frac{f(i,j)}{p(i)q(j)}, \tag{2}$$

where $\Lambda^{(2)}$ represents a two dimensional image and $f(i,j)$ represents the joint distribution of a traffic feature in p2p and non-p2p traffic; this joint distribution was computed by pairing up a p2p connection with its next non-p2p connection.

Mutual Information is a measure of the amount of information overlap between two feature distributions. It is a symmetric measure and does not require the two distributions to be continuous with respect to each other. Moreover, $I(X,Y) = H(X)$ in the limiting case of $X = Y$, while $I(X,Y) = 0$ when X and Y are independent. For the present problem, we employ the following normalized function of the mutual information measure, known as Variation of Information (VoI):

$$V(X,Y) = 1 - \frac{I(X,Y)}{H(X,Y)}, \tag{3}$$

where $H(X,Y) = -\sum_{i,j \in \Lambda^{(2)}} f(i,j) \log_2(f(i,j))$ is the joint entropy of X and Y.

We now use the proposed VoI measure to quantify the individual contributions of existing traffic features in improving the accuracy of a p2p traffic detector.

B. Evaluation of Existing Features

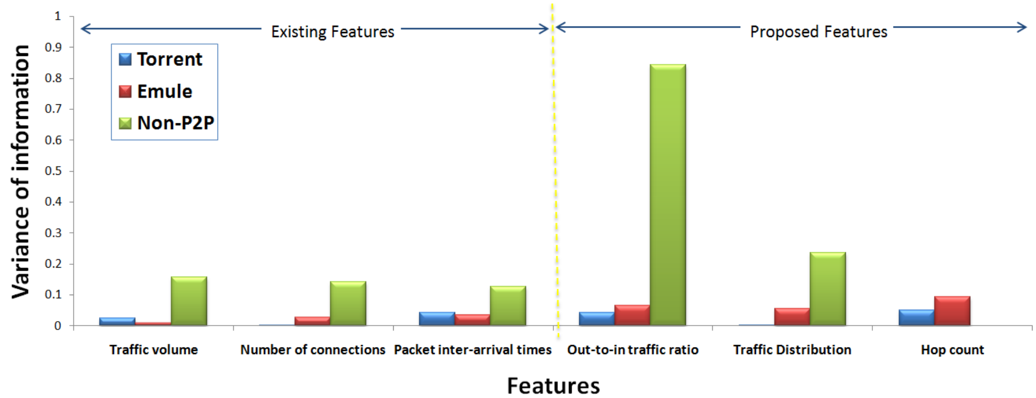
Prior studies have identified a rich set of approximately 42 distinct network layer traffic features for p2p traffic detection; see [37] and references therein. As a first step, we evaluated the individual contributions of each of these existing features for p2p traffic detection. As can be intuitively deduced, a good detection feature should vary considerably between p2p and non-p2p connections, while staying reasonably stable within a given (p2p or non-p2p) traffic class.

Figure 1(a) shows three existing features which provided the highest VoI divergence between p2p hosts and non-p2p hosts. Note that all three features are related to packet- or connection-level traffic volumes. Also, note that the divergence is not very high, mainly because other types of traffic– in particular, video traffic –was also providing high volumes with a number of connections to the server. Figure 1(a) shows the divergence between p2p connections and non-p2p connections for eight existing features that provided high enough VoI divergence to be considered for p2p connection detection. This detection is invoked after a host has been classified as a p2p host and we want to detect and regulate its p2p connections, without disturbing the non-p2p connections. It can be observed that existing connection-level features, although still relying mainly on traffic volume, can provide very high divergence between p2p and non-p2p connections. Hence, if a host is detected accurately, existing connection-level features can provide good estimation of the p2p connections originating from or terminating at the host.

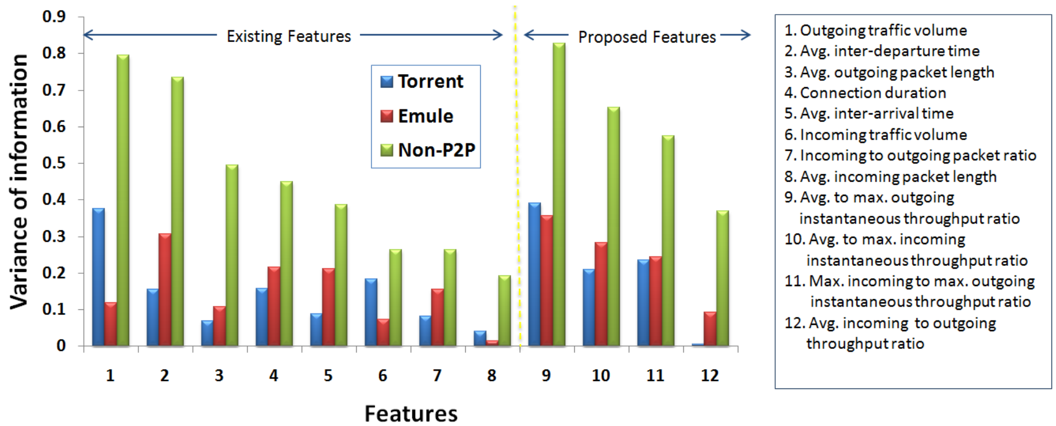
C. New Features for P2P Traffic Detection

We complement existing host- and connection-level features with a new set of robust traffic features. In this section, we describe these features and provide intuitive and empirical evidence to support their selection.

1) Outgoing-to-incoming Traffic Ratio: P2p applications simultaneously operate in both client and server modes. Therefore, while downloading a file, they are also serving/uploading files to the peers. This results in higher outgoing-to-incoming traffic ratio for p2p hosts. This behavior is uncharacteristic for non-p2p hosts which typically exhibit a high degree of disparity between incoming and outgoing traffic rates. This disparity arises as a consequence of the worldwide web's information pull model which induces incoming traffic rates that are significantly higher



(a) Divergence between hosts



(b) Divergence between connections

Figure 1. Variation of information (VoI) in distinguishing host- and connection-level features.

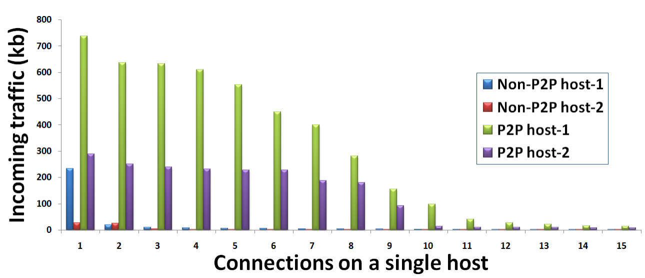


Figure 2. Incoming traffic distributions of p2p and non-p2p hosts.

than outgoing rates. In our evaluation dataset, we observed that on average p2p hosts had five times higher outgoing-to-incoming traffic ratio than non-p2p hosts. This result is also supported by the divergence values in Figure 1(a) which show that this feature's information divergence is approximately 5 times more than the best existing feature [Traffic volume]. Thus outgoing-to-incoming traffic ratio offers a very promising feature to improve the accuracy of p2p host detection.

2) Traffic Distribution: In a typical p2p application, only a fraction of connections have active file transfers at varying rates with peak transfer rates close to the mean due to peer clustering. In case of non-p2p applications, either the applications share their bandwidth fairly (which results in a flat distribution) or some applications consistently consume more bandwidth than the others (with huge variance among connections). This observation is shown pictorially in Figure 2 for 15 connections on two p2p and two non-p2p hosts. Clearly, non-p2p traffic's histogram is noticeably flatter than the p2p traffic histogram. Therefore, the traffic distribution feature should be able to distinguish p2p and non-p2p hosts. This is the reason that the traffic distribution feature provides almost twice the amount of divergence than was observed by the best existing host-level feature.

3) Geographical Diversity: Due to the widespread usage of common Content Distribution Networks (CDNs) by many web services (e.g., webservers, search engines, streaming video servers, FTP servers, etc.), we observed that non-p2p hosts generally use network services that are situated relatively close to their ISP's core network. On the other

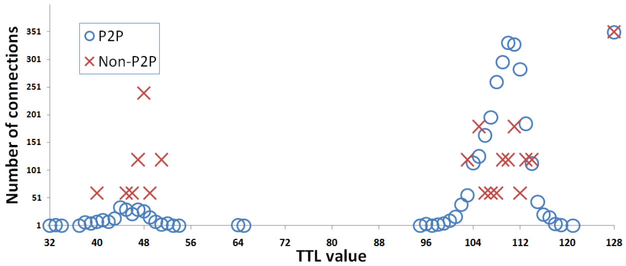


Figure 3. Distribution of IP TTL values for p2p and non-p2p hosts; large number of connections having TTL value 128 have been truncated for clarity.

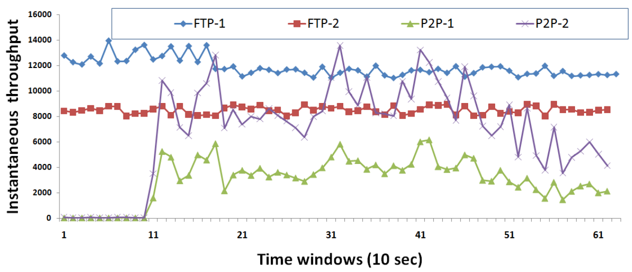


Figure 4. Instantaneous throughput of p2p (BitTorrent) and non-p2p (FTP) file sharing connections.

hand, p2p applications connect to peers which are placed at geographically distributed locations. As a consequence, inter-connection TTL values observed in p2p traffic fluctuate much more rapidly than the inter-connection TTL values for non-p2p hosts. In order to show that geographical diversity is a good feature to identify p2p hosts, Figure 3 plots the TTL values versus the number of connections for over 5000 p2p and 5000 non-p2p connections. This result confirms that the TTL value for the p2p hosts is more scattered than the non-p2p hosts. Figure 1(a) shows that the TTL feature offers a divergence comparable to existing features. (We defer discussion on possible attacks on this feature to Section VII.)

4) Instantaneous Throughput: As a precursor to p2p host detection, we also identified a set of distinguishing network layer features for p2p connection identification on a p2p host. In particular, we observed that the underlying peering principles of p2p file sharing protocols result in a per-connection throughput behavior which is significantly different from non-p2p traffic. For instance, Figure 4 shows the instantaneous throughput of p2p (BitTorrent) and non-p2p (FTP) file sharing connections over 61 windows of 10 seconds each. The obvious difference between the throughput behaviors is observed because p2p applications employ several mechanisms for peer selection such as connection shuffling and optimistic chocking/unchoking. Furthermore, the relationship among peers continuously changes due to high churn rate in p2p networks. Consequently, the incoming and outgoing throughputs among p2p connections are quite

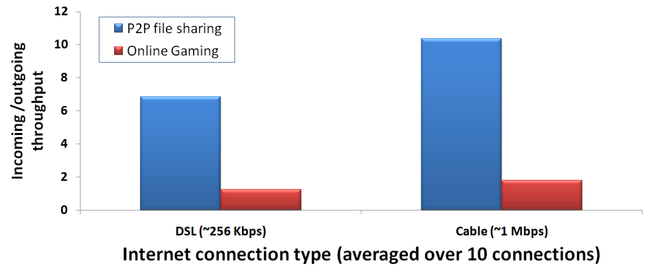


Figure 5. Incoming-to-outgoing throughput of p2p (EMule) and online gaming connections.

dynamic. On the other hand, bandwidth hungry client-server applications like FTP have relatively stable throughput as compared to p2p applications. Thus, instantaneous throughput based features offer a good discrimination between p2p and non-p2p connections, as is also shown quantitatively in Figure 4.

5) Incoming-to-Outgoing Throughput: Majority of p2p users use DSL/cable modems and have a tendency to choke the upload bandwidth so that their other Internet activities remain unaffected. We show this phenomenon by calculating the outgoing to incoming throughput ratio of 10 cable modem users and 10 DSL users. Figure 5 compares the throughput of p2p file sharing with another application that requires high incoming-to-outgoing throughput, namely online gaming. It can be seen that in comparison with online gaming users, p2p file sharing users have a higher throughput ratio because of upload bandwidth choking. As a consequence, this feature can be used to distinguish p2p file sharing connections.

D. Summary

We are now equipped with a robust set of privacy-preserving, network layer features that can be used to detect p2p hosts and connections. In the next section, we leverage these features in low complexity statistical frameworks and use ROC curves to evaluate the accuracies offered by these features on the evaluation datasets.

VI. Detection using Distinguishing Features

In this section, we leverage the distinguishing features identified in the preceding section to detect p2p hosts and connections. We propose a simple and low-complexity statistical detector that compares the learned statistical models of traffic features with the features observed in real-time using cross-correlation and log-likelihood tests. The output of these tests can be used to detect p2p traffic in real-time. We use $\approx 10\%$ of the datasets for training (the training set), and the rest is used for detection (the test set).

We employ two low-complexity statistical measures to leverage the distinguishing traffic features identified in the preceding section. For both measures, we first learn the p2p file sharing features' PMFs using the training set. The features observed in the unknown trace are then compared against the p2p traffic's PMFs using cross-correlation and log-likelihood tests described next.

A. Detection using Cross-Correlation Test

To leverage the identified traffic features for the present p2p detection problem, we need low-complexity mathematical measures that can quantify the degree of similarity of a learned probability distribution with the distribution observed at run-time. To this end, the well-known and widely-used cross-correlation measure from statistics [32] offers a natural and obvious choice to quantify the similarity between two random vectors.

To use the cross-correlation measure, we treat the ordered list of distinguishing features as a discrete random process, $\vec{Y}$, where each constituent random variable of the process corresponds to a distinct feature random variable. From the p2p traffic traces, we know the PMFs of each constituent random variable. We treat the distinguishing feature vector $\vec{X}$ from the unknown trace as a realization of this random process. To find the cross-correlation of the unknown realization with p2p trace realizations, we use the p2p features' PMFs to generate an ensemble of n realizations of the random process, say $\vec{Y}_i, i = 1, 2, ..., n$. We then generate a process realization $\vec{Y}$ by taking the ensemble average of each feature; i.e., for a feature indexed at k, $\vec{Y}[k] = \frac{1}{n}\sum_{i=1}^{n} \vec{Y}_i[k]$. We compute the cross-correlation of $\vec{X}$ with each $\vec{Y}$ as:

$$O(\vec{X}, \vec{Y}) = \sum_{k \in \phi} \vec{X}[k]\vec{Y}[k], \tag{4}$$

where ϕ is an ordered set of distinguishing feature random variables. High values of cross-correlation imply that the unknown data's features closely match the statistics observed in the training set. Low values of cross-correlation imply that the data potentially comprises non-p2p traffic.

B. Detection using Log-Likelihood Test

While the cross-correlation test was providing us reasonable p2p traffic and host detection accuracies, we observed that large mismatches in the learned and observed feature values tend to significantly bias the measure. To mitigate this problem, we complemented the cross-correlation measure with another low-complexity statistical similarity quantification measure known as log-likelihood. Assuming independence across features, the likelihood that the unknown realization $\vec{X}$ has been derived from the learned (p2p trace) random process $\vec{Y}$ is:

$$\begin{aligned} L(\vec{X}|\vec{\overline{Y}}) &= \log \prod_{k \in \phi} \left(\Pr\{\vec{Y}[k] = \vec{X}[k]\} \right) \\ &= \sum_{k \in \phi} \log \Pr\{\vec{Y}[k] = \vec{X}[k]\}, \end{aligned} \tag{5}$$

where ϕ is an ordered set of distinguishing feature random variables. As in the correlation measure, higher values of this measure imply a potential p2p host or connection, while non-p2p hosts/connections should have lower likelihood values.

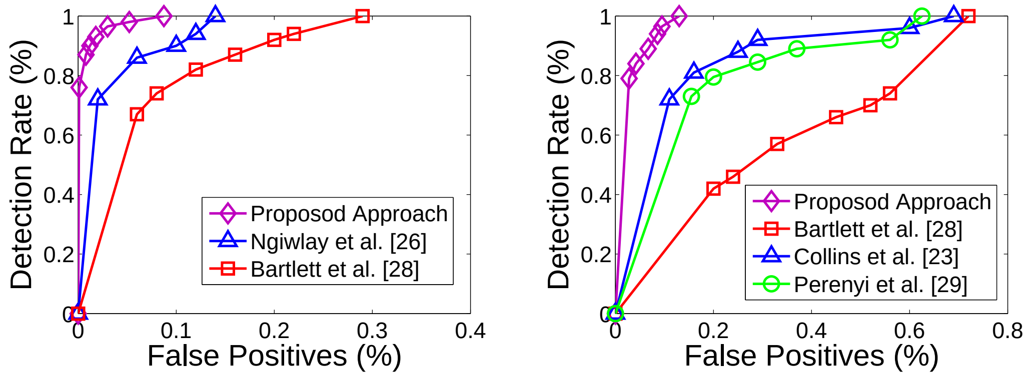
Before proceeding with detailed performance evaluation of a p2p detector employing the identified features and the above statistical measures, we acknowledge that it is possible to apply other statistical or information similarity measures on the learned and run-time traffic feature PMFs. We also experimented with other measures (e.g., information gain, information divergence, R^2, etc.) but observed that these measures could not induce a noticeable increase in p2p detection accuracy beyond what was already achieved by cross-correlation and log-likelihood measures. Moreover, most of these measures required complex mathematical operations (e.g., logarithmic calculations in information measures) which were unsuitable for real-time deployments. Therefore, we restrict ourselves to the two measures described in this section for performance evaluation in the following section.

C. ROC-based Performance Evaluation

We plot Receiver Operating Characteristics (ROC) curves to compare the accuracy of our proposed detector with existing p2p traffic/host detection methods. ROC curves are drawn with the detection (true-positive) rate on the y-axis and the false-positive rate on the x-axis. Each point on the ROC curve represents performance results for one configuration (or threshold value) whereas the curve represents the behavior for the complete set of configurations. When compared, the steepest and highest curve is considered the best as it approaches the highest detection rate with the lowest false-positive rate.

We detect a host/connection as p2p if either the cross-correlation or the log-likelihood detectors flag it as p2p. To generate ROC curves, we changed the detection threshold over a range of values and plotted the detection rate and false positive rate for each threshold. All performance evaluation is performed using the WIDE dataset and our encrypted dataset described earlier. Figure 6(a) shows the results of the proposed detector for host detection using 30 seconds of traffic. Figure 6(a) also compares the detection accuracy of the proposed approach with that of Ngiwlay et al. [26] and Bartlett et al. [28]. We evaluate [26] and [28] over 10 minutes of trace data. (The original papers which proposed these methods show that an acceptable detection accuracy can be achieved using 10 minutes of trace data.) It should also be noted that [26] only works for BitTorrent traffic. Therefore, for fair accuracy evaluation the results for [26] in Figure 6(a) are reported for BitTorrent traffic only; i.e., eMule traffic was excluded when [26] was evaluated.

It can be seen from Figure 6(a), that by using only 30 seconds of trace data, our detector provides a detection accuracy of 97.84% and a false positive rate of 4.01%. Performance comparison shows that the proposed method renders an improvement of 15% in detection rate, 10% in false positive rate, and 570 seconds over [26]. Similarly,



(a) Host detection

(b) Connection detection

Figure 6. ROC based performance evaluation of the proposed p2p host and connection detector.

Table IV
EMPIRICAL EVALUATION OF PROPOSED P2P TRAFFIC DETECTOR ON NATED TRAFFIC

	Detection Rate	**False Positive**
NATed trace	94.62%	4.87%
without NAT	93.27%	5.57%

our proposed method provides an improvement of 30% in detection rate, 20% in false positive rate, and 570 seconds over [28].

Figure 6(b) shows the results of the proposed detector for connection detection. The proposed classifier provides a detection rate of 93.27% and a false positive rate of 5.57% on the test set. A comparison of the proposed connection-based approach with [23], [28], [29] is also provided. It should be noted that the results for [28] are reported on 10 minutes of trace data for each connection (borrowed from the original paper), while for [23], [29] all the trace data for each connection was used as these are not real-time approaches. Figure 6(b) shows that for the detection of p2p connections, an improvement of 60% in detection rate rate, 30% in false positive rate, and 240 seconds in detection delay over [28] is observed. Similarly, 20% improvement in detection rate and false positive rates is recorded over [23]. Comparison with [29] shows an improvement of 30% in detection accuracy and 25% in false positive rate. It is evident from Figure 6(b) that the proposed approach provides much higher detection accuracy for a significantly lower detection delay than [23], [28], [29].

We also evaluate our proposed approach on NATed traffic. For traffic coming from a NAT server, we identified connections using source IP, destination IP, source port, and destination port. It should be noted here that we only use the port numbers to identify connections and do not use them for traffic identification. Table IV shows the results of the proposed detector for the NATed traffic. The results from

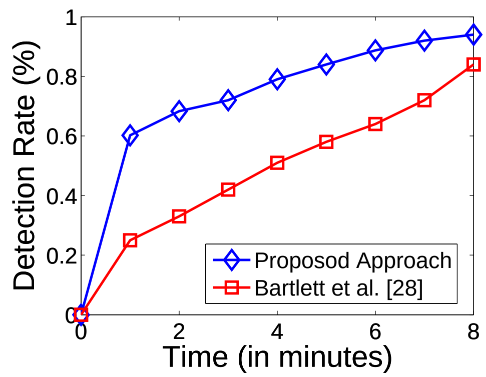


Figure 7. Time until detection (comparison with [23], [29] cannot be provided as [23] is an offline detection method and [29] requires at least 10 minutes of trace data for detection.)

Table IV clearly show that the proposed approach remains unaffected when a NAT or proxy server is present in the network.

In addition to having high accuracy, our proposed approach has low detection delay as compared to other approaches. To estimate detection delay, we identify the first p2p data packet between two hosts as the "start" time and then measure elapsed time until we detect that host as p2p. Figure 7 shows the sensitivity of the detection accuracy to the time delay in minutes. It can be seen from this figure that if only four minutes of trace data for each connection is used, we are able to identify about 80% of p2p connections. Similarly for eight minutes of trace data, about 94% of p2p connections are detected. These results show that the detection delay of the proposed approach is much better than the online detection technique of [28].

VII. Mimicry Attacks on the Proposed Approach and Countermeasures

To launch a mimicry attack to defeat our approach, a p2p host's traffic must have sufficient number of features that match those of a typical non-p2p host's traffic. By studying the divergence measures between p2p and non-p2p traffic types (given in Figure 1), one can determine which features of p2p applications should be modified to make it similar to a non-p2p application. Using this observation, we now discuss mimicry attacks on proposed features and discuss difficulties in realizing these attacks and potential countermeasures to circumvent them.

- A p2p host can defeat the proposed outgoing to incoming traffic ratio feature by uploading to and downloading from disjoint set of peers. However, uploading to and downloading from disjoint set of peers is contrary to the peer-to-peer model of p2p protocols which assists in thwarting the leechers.
- To defeat the incoming traffic distribution among connections feature, a p2p host will have to control the inflow of traffic from neighboring peers. Due to varying upload bandwidth and lack of control over network activity of neighboring peers, such a distributed coordination would require very careful design and high level of network control from the attacker.
- In order to defeat the geographical diversity feature, a p2p host should only communicate with peers at geographically co-located locations. However, such a p2p application would limit the number of peers it can communicate with. Furthermore, in order to defeat TTL distribution as a measure of geographical diversity, a p2p host will have to request its peers to communicate with it using a TTL distribution which is commonly used by non-p2p hosts. Such an attack on TTL distribution is indeed possible. A complex measure such as IP prefix matching can be used as a representative of geographical diversity to circumvent such an attack.
- Instantaneous throughput measure based features can be defeated by maintaining a near constant throughput with neighboring peers. However, as p2p hosts do not have control over the instantaneous outgoing throughput of neighboring peers, circumventing this feature will require a significant control over peers which is generally not possible in a p2p network.

Based on the above discussion, we conclude that a p2p host/application attempting to circumvent the proposed features will seriously compromise the performance of its underlying p2p application/protocol.

VIII. Conclusion

In this paper, we demonstrate that network layer features alone are sufficient to provide the accuracy that is expected from p2p traffic detectors. We proposed a network layer detector which, in addition to being accurate, fast, and robust against evasion, outperformed existing application and transport layer detectors on diverse evaluation metrics. We hence show that privacy-preserving, payload-oblivious p2p traffic detection is indeed possible and such detectors offer a pragmatic middle ground for the two extreme schools of thought on DPI-based traffic classification.

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