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Characterization of Tor Traffic using Time based Features

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Abstract: Traffic classification has been the topic of many research efforts, but the quick evolution of Internet services and the pervasive use of encryption makes it an open challenge. Encryption is essential in protecting the privacy of Internet users, a key technology used in the different privacy enhancing tools that have appeared in the recent years. Tor is one of the most popular of them, it decouples the sender from the receiver by encrypting the traffic between them, and routing it through a distributed network of servers. In this paper, we present a time analysis on Tor traffic flows, captured between the client and the entry node. We define two scenarios, one to detect Tor traffic flows and the other to detect the application type: Browsing, Chat, Streaming, Mail, Voip, P2P or File Transfer. In addition, with this paper we publish the Tor labelled dataset we generated and used to test our classifiers.

1 INTRODUCTION

Traffic classification technologies have experienced great advances over the last decade due to its application in systems like Quality of Service (QoS)s mechanisms or SIEM (Security Information and Event Management) tools. The industry as well as the research community have dedicated many efforts to the study of these technologies, developing several classification techniques (Nguyen and Armitage, 2008; Callado et al., 2009). However, the continuous growth of Internet and its offer of services, along with the latest trend to encrypt and/or disguise these services, makes traffic classification a great challenge for the Internet research community (Dainotti et al., 2012). One of the obstacles to traffic classification is encryption, a key technology to protect Internet users' freedom and privacy, providing them with anonymity and the means to protect themselves against network surveillance systems.

Tor (Dingledine et al., 2004) is currently the most popular privacy enhancing tool. It can anonymize the identity of users as well as their Internet activity by encrypting and tunneling the traffic through a distributed network of servers, known as Tor nodes.

In this paper we focus on the characterization of Tor traffic, that is, downgrading privacy to some extent by exposing the activity within the Tor traffic. Given a traffic flow, we aim to detect whether it is Tor traffic or not. Moreover, once we identify it as Tor, we also want to know what kind of application is running within the Tor flow: browsing?, chat?, file transfer?, etc. Our experiment relies on the assumption that different types of traffic have different time constrains, allowing us to characterize the traffic being routed through a Tor node. A clear example may be the time constraints of real time voice applications (VoIP), where we require a minimum bandwidth, but at the same time we have a maximum, i.e. we will not be able to transmit more bytes than we generate. In comparison, Audio Streaming applications will also have a minimum bandwidth, but the maximum will be determined by the server and network capacity. We believe that these differences should reflect on the time statistics, therefore we could use them to identify different traffic applications.

The novelty of our work is an approach chosen to analyze the traffic flows, we focus on *time*-related features only. In the literature we can find many papers using features extracted from flows, but none of them have focused exclusively on time based features. The authors in (Quinlan, 1993) use the size of the first n packets to detect Tor traffic. Authors in (Juarez et al., 2014; Bai et al., 2008) use a combination of time features and other packet based features like size, ports, flags, etc. Moreover, they focus on particular applications like Skype and SSH. Our main objective is to classify traffic into different types, where one type of traffic will include different applications, e.g. we captured Voip traffic from Hangouts, Facebook and Skype.

Our Contribution: Our contribution in this pa-

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per is twofold. First, we propose a set of *time*-based features to identify and characterize Tor traffic, and we prove that using *time*-based features only we can identify and characterize Tor traffic to some extent. Second, we study the impact of the length of the flows in the efficiency of the traffic classification, according to our experiments, 15s is the optimal length. In addition, we publish a labelled dataset of Tor traffic along with the tool we used to generate it. The dataset contains 8 different labels, corresponding to the 8 different types of traffic captured: browsing, audio streaming, chat, video streaming, mail, VoIP, P2P and file transfer. We choose only time-related features to expedite the efficiency and to ensure an encryption independent traffic classifier.

2 RELATED WORK

Tor has been the subjective of many research papers, focusing many of them on compromising Tor's anonymity or improving its performance (Chakravarty et al., 2014; AlSabah et al., 2012). Another topic of interest related with the Tor network, and closer to the problem we address, is the analysis of the Tor traffic (Bai et al., 2008; Chaabane et al., 2010; Ling et al., 2014; AlSabah et al., 2012), but in almost all of cases the analysis is performed within a Tor node. In fact, we haven only found one paper that addresses the problem of characterizing Tor traffic observing the network traffic between the client and the entry node (He et al., 2014). In the following paragraphs, we review some of these works.

In (Juarez et al., 2014), the authors exploit the user's browsing behaviour, along with location data and the version of the browser to execute a website fingerprinting attack. The main objective of the paper differs from ours, while they try to identify the different websites a user is browsing, we aim at identifying the traffic category, which in this case would be browsing. Moreover, they conclude with around 37% false positives.

In (Chakravarty et al., 2014) Chakravarty *et al.* present an attack against the Tor network, with the objective of revealing the identity (IP address) of the clients. The paper proposes an active traffic analysis attack based on deliberately perturbing the characteristics of user traffic at the server side (colluding server), and observing a similar perturbation at the client side through statistical correlation. Their method achieves an accuracy of 100% in in-lab tests, and more than 81% in real-world experiments.

AlSabah *et al.* (AlSabah et al., 2012) propose a QoS mechanism to improve the performance of the Tor network, distinguishing between Bulk Transfer (e.g. Bittorrent), Interactive (e.g. web traffic) and Streaming traffic. As classifiers they use Tor *Circuit Lifetime*, *Data Transferred*, *Cell inter-arrival times* and *Number of Cells sent recently*. They test different algorithms (Naiv̈e Bayes, Bayesian Networks, and Decision Trees) on an artificial dataset (Bayesian Networks, 3 classes, over 90% accuracy) , and in a live experiment (Naiv̈e Bayes, Bulk and Interactive classes, 77% accuracy).

In (Bai et al., 2008) Bai *et al.* propose a fingerprinting method to identify Tor and Web-Mix networks. Their method uses specific strings, packet length and frequency of the packets. They test their method on simulated networks obtaining more than 95% of accuracy in both systems (Tor and Web-Mix).

In (Chaabane et al., 2010) Chaabane *et al.* use Deep Packet Inspection (OpenDPI) to analyze the traffic from a group of 6 exit nodes deployed for that purpose. Their results show that more than 50% of the traffic belongs to Bittorrent applications. Although OpenDPI is not able to identify encrypted connections, around 30% of the total traffic, the authors claim that these connections also belong to P2P, after analyzing the usage of encryption in Bitorrent connections.

In (Ling et al., 2014) the authors present an analysis of Tor traffic using an Intrusion Detection System (IDS). The papers presents the results on an analysis done using Suricata, and a commercial IDS rule-set (ETPro). According to their results, 10% of the Tor traffic is malicious, i.e. it triggers an alert. From that 10%, more than 70% of the alerts where triggered by P2P traffic.

In (He et al., 2014) the authors propose a method based on HMM (Hidden Markov Models) to classify encrypted Tor traffic in 4 categories: P2P, FTP, IM and Web (anything else is unknown). As classifiers (features) they use burst volumes and directions, extracted from Tor flows. They use HMM to build ingress and egress models of the different application types (P2P, FTP, IM and Web). They obtain a maximum overall accuracy value of 92%.

Authors in (Serjantov and Sewell, 2003) discussed about the anonymity in connection-oriented system by outlining the attack scenarios against anonymous web browsing. By running web clients with a small additional latency (without adding dummy traffic to minimize bandwidth requirement), they design a threat model for a *passive attacker* to identify the browsing activities of the user. They measure the number of simultaneous connections per second to be initiated in order to provide anonymity. It appears that 100 users with 2-4 network links provide 92%

compromised connections (poor anonymity) whereas a scenario with 20 users with 200 connections ends up with only 2.5% compromised connection, that is, probability of a very high anonymous system. Nonetheless, they did not consider any active attacks related to connection-based anonymity systems, specially attacks related to tracing source and destination of an established connection (that was solved later in (Shmatikov and Wang, 2006)).

In (Mittal et al., 2011), Mittal *et al.* combine information extracted from the forwarding capacity between intermediate relay Tor nodes to link connections from the same initiator with 98.5% accuracy. Circuits sharing the same bottleneck relay yield highly correlated throughput. Applying attacks on the live Tor network they revealed the identities of the guard relays. However, authors use their self-generated circuit to avoid non-participating clients. All the experiments were done within only 25 Tor relays and regarding the guard relay they consider only burst sized data. This throws a big question about the scalability of the attack.

Low latency mix networks are vulnerable to traffic analysis due to inherent statistical characteristics of packet data stream and stringent latency requirement incurred by interactive applications. Note that even if the established communication channel and payloads are *encrypted* and padded to hide payload size, Inter packet arrival time (time differences between consecutive packets) cannot be *concealed* because of the low latency requirement of the application. One of the papers that focus on the same area of timing analysis is (Shmatikov and Wang, 2006)- where the authors find a correlation of inter-packet arrival time and packet flows in order to identify network traffic in mix-networks. By modifying packet flows they were able to fingerprint origin (e.g. browser) and destination (e.g. destination) of IP traffic. To get rid of this privacy attack, authors propose adaptive padding algorithm- where an expected inter-packet interval (EIPI) is randomly chosen in order to destroy natural fingerprints. As the experiment shows- the correlation coefficient between two links of the same path based on Inter-packet intervals lies to 0.9 while 0.3 for unrelated links. Introducing adaptive padding reduces correlation within the same flow to 0.2-0.4.

The very first attack on Tor network anonymity was proposed by Aaron *et al.* in (Johnson et al., 2013), where authors show that typical Tor users are more vulnerable to compromise than expected in the prior works. They present a security model of a realistic Tor path simulator that includes users, adversaries, Tor network relays, group of Internet exchange points and Autonomous Systems (AS). Their results show that anonymity of the users can be broken 80% (of all users) by a Tor-relay adversary within 6 months and *completely* by a single AS adversary within 3 months. However, unlike (Johnson et al., 2013; Shmatikov and Wang, 2006), we do not consider any attack models, circuit clogging, or network adversaries, that is beyond the goal of this paper. Instead, we focus on in-depth correlation between network-bound traffic flow interval and the characteristic of Internet applications.

2.1 Comparing with Related Work

Based on our study, the papers closer to our work were done by AlSabah *et al.* (AlSabah et al., 2012), Bai *et al.* (Bai et al., 2008), and Luo*et al.* (He et al., 2014). Figure 1 shows a comparison between these papers and our proposed method at a glance. The first paper (AlSabah et al., 2012) is based on the onion routers to extract cells information such as circuit lifetime, cell inter-arrival times and the number of cells sent recently from the network packet but since one packet may contain many cells, so it is not possible to extract cell information from network traffic. The second research paper (Bai et al., 2008) is focused on the detection of Tor and Web-Mix networks. They did not extend their work to characterization based on the type of application. The third paper (He et al., 2014), the closest one to our proposal, is focused on the identification of only four protocols: P2P, FTP, IM and Web which we distinguish between 8 different types. Moreover, to test their proposal they set up a private Tor network, whereas we used traffic captured from the public Tor network.

3 DATASET GENERATION

One of the contributions of this paper is the labelled Tor traffic dataset that we used in our experiments. To generate a representative dataset of real-world traffic we defined a set of tasks, assuring that our dataset is rich enough in diversity and quantity. We created accounts for users Alice and Bob in order to use services like Skype, Facebook, etc. The dataset contains 8 types of traffic (browsing, chat, audio-streaming, video-streaming, mail, VOIP, P2P and File Transfer) from more than 18 representative applications (e.g., facebook, skype, spotify, gmail etc.).

Figure 2 shows the configuration we have used to generate the dataset. We have used Whonix (https://www.whonix.org), a ready-to-use Linux OS configured to route all traffic through the Tor network. The Whonix distribution is composed of two virtual machines, the gateway and the workstation. As we

Research	Type	Features	Applications	Protocols
AlSabah *et al.*	Cell information	Cell features such as circuit lifetime, cell inter-arrival times, number of cells sent recently from the network packet	-	-
Bai *et al.*	Network Traffic	Traffic features such as packet length and frequency of the packets' sending time	-	-
Luo *et al.*	Network Traffic	burst volumes such as total size of all packets and directions	-	P2P, FTP, IM , Web
Proposed method	Network Traffic	time-related features	Browsing, Email, Chat, Audio - Streaming, Video Streaming, File Transfer, P2P APP. , VoIP	HTTP, HTTPS, Web, SMTP/S, PoP3/SSL, P2P, IMAP/SSL, SFTP, FTPS

Figure 1: Comparison of related works.

Table 1: Contents of the Datasets (number of samples).

	Scenario A			Scenario B								
	TOR	NOTOR	**Total**	Bro	Ema	Chat	Aud	Vid	FT	VoIP	P2P	**Total**
10s.	8044	59790	67834	1604	282	323	721	874	864	2291	1085	8044
15s.	5631	48123	53754	1194	194	249	510	617	590	1544	733	5631
30s.	3130	43892	47022	694	111	153	332	364	311	790	375	3130
60s.	1723	41376	43099	411	60	90	190	196	165	413	198	1723
120s.	969	38285	39254	239	34	151	119	105	86	225	110	969

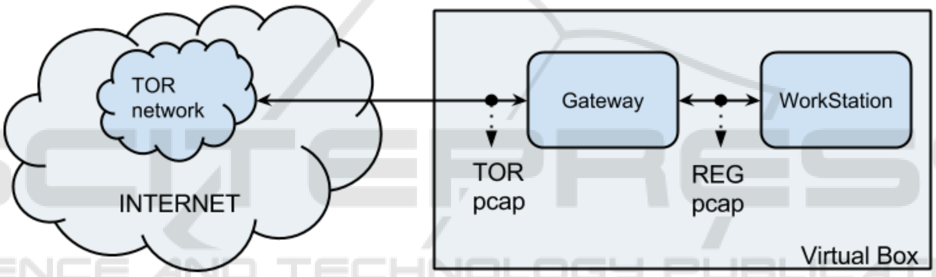


Figure 2: Tor capture scenario.

can see in Figure 2, the workstation connects to the Internet through the gateway virtual machine, which in turn routes all the traffic through the Tor network. With this configuration, using the Tor network at the workstation virtual machine becomes transparent. We captured the outgoing traffic at the workstation and the gateway simultaneously, collecting a set of pairs of .pcap files: one *regular* traffic *pcap* (workstation) and one Tor traffic *pcap* (gateway) file. Later, we labelled the captured traffic in two steps. First, we processed the *.pcap* files captured at the workstation: we extracted the flows, and we confirmed that the majority of traffic flows were generated by application X (skype, ftps, etc.), the object of the traffic capture. Then, we labelled all flows from the Tor *.pcap* file as X. The reason behind this method for labelling the Tor traffic is that Tor is a circuit oriented protocol: all traffic from the gateway to the entry node will be encrypted and sent through the same connection.

Therefore the flows generated from the Tor traffic captured will *look the same*, i.e. same source ip, destination ip, source port, destination port and protocol (TCP), we will not be able to distinguish them. But since we are working in a controlled environment, and we are executing one application at a time, lets say application Y, most of the Tor flows will belong to this application Y. As a consequence of our la labelling process our training and validation datasets will include some *noise*, flows of type X labelled as type Y, which in turn it will affect the accuracy of our classifiers. In Table 1 we have a description of the contents of the different datasets, in terms of number of samples of each type (label). Following, we give a detailed description of the different types of traffic generated:

Browsing: Under this label we have HTTP and HTTPS traffic generated by users while browsing (Firefox and Chrome).
Email: Traffic samples generated using a Thunderbird client, and Alice and Bob Gmail accounts. The clients were configured to deliver mail through SMTP/S, and receive it using POP3/SSL in one client

and IMAP/SSL in the other.

Chat: The chat label identifies instant-messaging applications. Under this label we have Facebook and Hangouts via web browser, Skype, and IAM and ICQ using an application called pidgin (https://pidgin.im).

Audio-Streaming: The streaming label identifies audio applications that require a continuous and steady stream of data. We captured traffic from Spotify.

Video-Streaming: The streaming label identifies video applications that require a continuous and steady stream of data. We captured traffic from Youtube (HTML5 and flash versions) and Vimeo services using Chrome and Firefox.

File Transfer: This label identifies traffic applications whose main purpose is to send or receive files and documents. For our dataset we captured Skype file transfers, FTP over SSH (SFTP) and FTP over SSL (FTPS) traffic sessions.

VoIP: The Voice over IP label groups all traffic generated by voice applications. Within this label we captured voice-calls using Facebook, Hangouts and Skype.

P2P: This label is used to identify file-sharing protocols like Bittorrent. To generate this traffic we downloaded different .torrent files from the Kali linux distribution (https://www.kali.org) and captured traffic sessions using the Vuze (https://www.vuze.com) application. We used different combinations of upload and download speed to accommodate a more general behaviour.

3.1 Flow and Features Generation

We use a common definition of flow, where a flow is defined by a sequence of packets with the same values for {*Source IP*, *Destination IP*, *Source Port*, *Destination Port* and *Protocol (TCP or UDP)*}. In the case of Tor traffic, all flows will be TCP, since it does not support UDP. Along with the flow generation we calculate the features associated with each flow. In most of the previous publications the authors use Netmate (Nguyen and Armitage, 2008),(Aghaei-Foroushani and Zincir-Heywood, 2015) to extract the traffic flows and features. But Netmate cannot generate all the features we need, and it is not officially available anymore. For this experiment, we used a new application, the ISCXFlowMeter (ISCXFlowMeter, 2016) to generate the flows and calculate all necessary parameters.

The FlowMeter generates bidirectional flows, where the first packet determines the forward (source to destination) and backward (destination to source) directions, hence the statistical *time*-related features are also calculated separately in the forward and reverse direction. Note that TCP flows are usually terminated upon connection teardown (by FIN packet) while UDP flows are terminated by a flow timeout. The flow timeout value can be assigned arbitrarily by the individual scheme e.g., 600 seconds for both TCP and UDP in (Aghaei-Foroushani and Zincir-Heywood, 2015). In this paper, we also study several flow timeout (FT) values to determine the impact of the flow timeout on the final results. In particular, we set the duration of flows to 10, 15, 30, 60 and 120 seconds.

As previously mentioned in Section 1, we focus on *time*-related features. When choosing *time*-related features, we consider two different approaches. In the first approach we measure the time, e.g. time between packets or the time that a flow remains active. In the second approach, we fix the time and measure other variables, e.g., bytes per second or packets per second. Following we have a list and description of the features measured, a total of 23 values:

fiat: Forward Inter Arrival Time, the time between two packets sent forward direction (mean, min, max, std).

biat: Backward Inter Arrival Time, the time between two packets sent backwards (mean, min, max, std).

flowiat: Flow Inter Arrival Time, the time between two packets sent in either direction (mean, min, max, std).

active: The amount of time time a flow was active before going idle (mean, min, max, std).

idle: The amount of time time a flow was idle before becoming active (mean, min, max, std).

fb_psec: Flow Bytes per second.

fp_psec: Flow packets per second.

duration: The duration of the flow.

As one can see, except the duration, which shows the total time of one flow, there are six groups of features. The first three groups are namely: -fiat, -biat, and -flowiat, and are focused respectively on the forward, backward and bi-directional flows. The fourth and fifth groups of features, are calculated regarding to the idle-to-active or active-to-idle states and are named -idle and -active. Finally, the last group focuses on the size and number of packets per second and is named -psec feature.

4 EXPERIMENTS

To test our time-based features we have defined 2 different experiments. The first experiment corresponds

Table 2: Results of feature selection used in the Validation experimen.

Scenario A 15s. Dataset			Scenario B 15s. Dataset		
SE+BF	**IG+RK**		**SE+BF**	**IG+RK**	
min_flowiat	1.1815	flowBytesPerSecond	duration	0.31552	mean_biat
std_biat	1.1617	mean_fiat	flowBytesPerSecond	0.30565	max_biat
mean_biat	1.1188	mean_flowiat	mean_flowiat	0.29642	std_biat
max_biat	1.1179	flowPktsPerSecond	max_flowiat	0.28279	min_flowiat
	1.0795	max_fiat	min_flowiat	0.26069	flowBytesPerSecond
	1.0582	max_flowiat	mean_fiat	0.25335	std_fiat
	1.0403	max_biat	std_fiat	0.25173	mean_fiat
	0.9683	std_flowiat	max_fiat	0.24698	mean_flowiat
	0.9552	mean_biat	min_fiat	0.24666	std_flowiat
	0.9517	min_biat	min_biat	0.23993	flowPktsPerSecond
	0.9128	std_fiat		0.23816	duration
	0.825	std_biat		0.23676	max_fiat
	0.7877	min_fiat		0.19956	max_flowiat
	0.7289	min_flowiat		0.1893	min_biat
	...	...		...	...

to the Scenario A, and focuses on the detection of Tor traffic. The second experiment, Scenario B, focuses on the characterization of Tor traffic, i.e., identifying applications within Tor traffic. Following, we describe the scenarios in more detail:

Scenario A: To create this scenario we have merged 2 different datasets, the Tor dataset presented in this paper and an available public dataset of encrypted traffic generated by Draper-Gil *et al.* in (Draper-Gil et al., 2016), which includes the same applications on the same network. We generated the flows and extracted our proposed time-based features from each dataset, and we labelled all flows from the Tor dataset as Tor, and all flows from Draper-Gil *et al.* in (Draper-Gil et al., 2016) as NonTor. We merged and flushed both groups of labelled flows and used them as input to the Scenario A experiment. The use case in this scenario is an application that, given a set of time-based features (Table 2) extracted from an encrypted traffic flow (input), will tell us if it belongs to Tor (output).

Scenario B: In this scenario, we have used only the Tor dataset presented in this paper. As we discussed in Section 3, we generated the flows from the .pcap files captured at the gateway, and we labelled them (Browsing, Audio, CHAT, Mail, P2P, FT, VOIP, and Video) according to application executed on the workstation (See Figure 2). The use case in this scenario is an application that given a set of time-based features (Table 2) extracted from a Tor flow (input), will detect (label) the application type running in this flow (output).

As we mention in Section 3.1 that we will use 5 different flow-timeout values: 10s., 15s, 30s, 60s and 120s. Therefore, for each scenario (scenarios A and B) we will have 5 different datasets, one for each flow timeout value.

4.1 Feature Selection and Validation

To run the experiments we used Weka (Hall et al., 2009), an open source implementation of a collection of machine learning algorithms. We have divided our analysis process in two steps, testing and validation, dividing our datasets accordingly: 80% for testing and 20% for validation.

In the first step of the analysis we applied different feature selection algorithms to each testing dataset (10s, 15s, 30s, 60s, and 120s), and measured its performance in terms of weighted average precision and recall. In the Table 2 we can see the results of the feature selection for each scenario (for readability reasons, we only show the combinations used in the final step, the validation process), whereas Table 3 presents the testing results.

In the second step, we evaluated the best combination of features + dataset using the corresponding validation dataset. These results are presented in figure 3 and discussed in Section 5. Our combination algorithms for feature selection are CfsSubsetEval+BestFirst (SE+BF) and Infogain+Ranker (IG+RK).

In the Scenario A, as we only have two classes (Tor and NonTor), we selected the ZeroR, C4.5 and KNN algorithms. But, in the Scenario B we have eight classes, therefore we chose Random Forest, C4.5 and KNN as algorithms to build our classifier. We executed the tests using 10 fold evaluation on the test (80%) datasets, and the final evaluation using the

Table 3: Training results for Scenarios A and B.

Scenario A

	Zero R				C4.5				KNN			
	SE+BF		IG+RK		SE+BF		IG+RK		SE+BF		IG+RK	
	PR	RC	PR	RC	PR	RC	PR	RC	PR	RC	PR	RC
10s.	0.777	0.881	0.777	0.881	0.950	0.950	0.973	0.973	0.940	0.940	0.953	0.953
15s.	0.801	0.895	0.801	0.895	0.976	0.976	0.987	0.987	0.967	0.967	0.971	0.970
30s.	0.871	0.933	0.871	0.933	0.979	0.979	0.987	0.987	0.975	0.975	0.976	0.976
60s.	0.922	0.960	0.922	0.960	0.985	0.986	0.990	0.990	0.981	0.981	0.983	0.983
120s.	0.951	0.975	0.951	0.975	0.988	0.988	0.990	0.991	0.985	0.985	0.988	0.988

Scenario B

	Random Forest				C4.5				KNN			
	SE+BF		IG+RK		SE+BF		IG+RK		SE+BF		IG+RK	
	PR	RC	PR	RC	PR	RC	PR	RC	PR	RC	PR	RC
10s.	0.760	0.762	0.842	0.840	0.728	0.732	0.790	0.790	0.675	0.676	0.702	0.704
15s.	0.833	0.831	0.841	0.836	0.797	0.798	0.796	0.796	0.688	0.691	0.704	0.707
30s.	0.799	0.799	0.808	0.808	0.760	0.760	0.754	0.756	0.656	0.660	0.664	0.666
60s.	0.744	0.748	0.750	0.754	0.696	0.698	0.690	0.695	0.612	0.611	0.615	0.618
120s.	0.725	0.728	0.741	0.743	0.665	0.664	0.674	0.675	0.595	0.600	0.607	0.609

SE+BF is CfsSubsetEval+BestFirst
IG+RK is Infogain+Ranker
PR is Precision
RC is Recall

validation datasets (20%) as *supplied test set*.

To evaluate the quality of our classification processes, we used two common metrics: Precision (Pr) or Positive Predictive value and Recall (Rc) or Sensitivity. The Precision represents the ratio of correctly classified instances (TP), lets say X, in front of all the instances classified as X (TP+FP). Whereas the Recall represents the ratio of correctly classified instances (TP), lets say Y, in front of all Y instances (TP+FN).

$$Pr = \frac{TP}{TP+FP} \qquad Rc = \frac{TP}{TP+FN}$$

5 ANALYSIS OF THE RESULTS

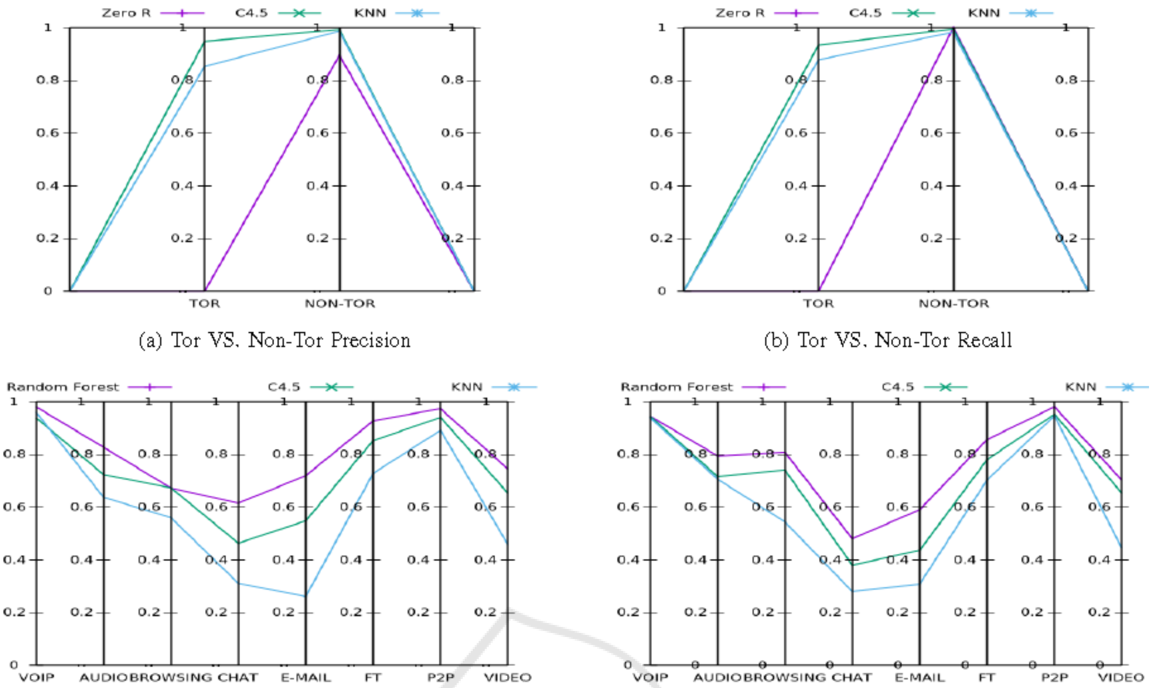
In this section we analyze the results obtained in the testing and validation experiments, for each scenario. The results of the testing experiment are presented in Tables 2 ans 3, and the results of the validation experiments are shown in Figure 3.

5.1 Analysis of Scenario A

The results of the feature selection of Scenario A are presented in Table 2. The results of the combination CfsSubsetEval+BestFirst (SE+BF) are almost identical in all 5 datasets, reducing the number of features from 23 to 5. In the case of Infogain+Ranker (IG+RK), the result is a ranked list of the 23 features. To decide the number of features to include in the testing experiments, we looked for a large decrease of weight between two consecutive features. In the case of the features presented in Table 2, the weight of the last selected feature, the 14th (min_flowiat), is 0.7289 and the weight of the next one is 0.4998 (duration), a large difference compared with the previous ones.

We used the results from the feature selection algorithms to test different machine learning algorithms (ZeroR, C4.5 and KNN) using 10 fold cross validation and we measured the weighted average precision and recall. The results are presented in Table 3. Since it is a binary classification (Tor vs. NonTor), we used ZeroR to establish a lower boundary reference. The Zero R classifier will always classify a sample as the most common class in the dataset, that explains why its results improve with the flow timeout value: the longer the flow timeout, the more unbalanced is the dataset (we have less Tor samples), as we can see in Table 1. The results obtained in this step of the process, Table 3, show that in all cases C4.5 and KNN are better that Zero R, the lower boundary.

From the results, it seems that longer timeout values (120s dataset) provide better results than shorter ones (e.g., 15s dataset), but this trend also shows that longer timeout values make our results closer to the lower bound (Zero R). As example, using C4.5 and IG+RK, the difference in precision and recall for 10s.



(a) Tor VS. Non-Tor Precision

(b) Tor VS. Non-Tor Recall

(c) Tor Characterization Precision

(d) Tor Characterization Recall

Figure 3: Precision and Recall of Validation experiments.

is 0.196 and 0.092, whereas for 120s is 0.041 and 0.015 respectively. With these results, our candidate for the validation experiments should be either the 10s. or the 15s. dataset. But we will choose the 15s. dataset to match the result of the scenario B. In a practical scenario, it would make sense to have only one flow generator, and use its result as input to detect and classify Tor traffic:

- Zero R: the results are independent of the set of features they only depend on the distribution of samples. We used 15s dataset to compare with the C4.5 and KNN results.
- C4.5: 15s dataset and IG+RK.
- KNN: 15s dataset and IG+RK.

Finally, we used the validation dataset to calculate the precision and recall of the best combinations from the testing process. The results are presented in Figure 3 (a,b), showing the values of precision and recall for each class (Tor, nonTor). The best results are obtained using the C4.5 algorithm, with both precision and recall above 0.9. The results for Zero R are 0 and 0.895 for precision and 0 and 1 for recall. Which means that the Zero R classifier will not detect any Tor sample, whereas our C4.5 classifier will be able to detect 93.4% of all Tor samples (recall), and every time it labels one sample as Tor, it will do it with 94.8% probability of success (precision). Regarding nonTor samples, by definition the Zero R classifier will detect 100% of nonTor samples (it labels everything as non-Tor, recall = 1), and its labels will be 89.5% accurate (precision). Our C4.5 classifier will detect 99.4% (recall) of the nonTor samples, and its nonTor labels will be 99.2% accurate (precision). Following we have the confusion matrix for the C4.5 algorithm, the one with best performance:

```
=== Confusion Matrix ===
 a     b   <--
1053    74 | a = Tor
 58   9567 | b = nonTor
```

The confusion matrix of our classifier shows us the number of samples correctly classified (matrix diagonal), and the number of samples incorrectly classified, specifying the label with which they were confused. In this case we only have two labels, therefore Tor labels will always be confused with Non-Tor and vice versa.

5.2 Analysis of Scenario B

The Scenario B focuses on the characterization of Tor traffic in 8 different types of traffic (Section 3). The results of the feature selection are presented in Table 2. In this case, using SE+BF we reduced the number of features from 23 to 10, and using IG+RK from 23 to 15. In the IG+RK case presented in Table 2, the

16th (min_fiat) feature is weighted with 0.17356 and the next feature (min_active) with 0.02018. Interestingly, in all cases the features discarded by the IG+RK are the ones measuring the idle and active features.

After the feature selection process, we tested the results obtained with the 3 different algorithms: Random Forests, C4.5 and KNN, using 10 fold cross validation. The results are presented in Table 3 and show a clear relation between the flow timeout and the efficiency of the algorithms tested: the shorter the flow timeout, the better the results, with an optimal value of 15s, i.e. with a flow-timeout lower than 15s. the results are worse. Regarding the efficiency of the algorithms, Random Forest obtained the best results, in combination with the features selected by the IG+RK algorithm. From the results presented in Table 3 we selected the following combination for the validation experiment:

- Random Forest: 15s. dataset and IG+RK.
- C4.5: 15s. dataset and SE+BF. The results are similar with both feature selection algorithms, but for efficiency reasons we chose SE+BF, it requires less features.
- KNN: 15s. dataset and IG+RK.

Finally, we used the validation dataset to evaluate the precision and recall of the different algorithms. The results are presented in Figure 3 (c and d), showing the values of precision and recall for each of the 8 classes. As the Figure clearly shows, the best results are obtained with Random Forest, and if we calculate the weighted average (see Section 4), we obtain the following values 0.843,0.788,0.705 for precision and 0.838,0.790,0.705 for recall (Random Forest, C4.5 and KNN respectively). If we focus on the particular values for each class (type of traffic), we can group the classes in two sets, depending on the results obtained. In the first group, we have the classes with good precision and recall results: VOIP, P2P, AUDIO, FT and VIDEO. In another group, we have the classes our classifier fails to obtain good results: BROWSING, CHAT and E-MAIL. To have a better understanding of the results, following we have the confusion matrix resulting of the Random Forest experiment:

```
=== Confusion Matrix ===
  a   b   c   d   e   f   g   h <--
292   1  11   0   0   2   2   1 |  a = VOIP
  1  81  15   1   2   0   0   2 |  b = AUDIO
  2   9 193  12   3   1   0  19 |  c = BROWSING
  0   1  24  24   1   0   0   0 |  d = CHAT
  0   3  10   0  23   1   0   2 |  e = MAIL
  0   0   8   1   2 101   1   5 |  f = FT
  1   0   1   0   0   0 144   1 |  g = P2P
  2   3  25   1   1   4   1  87 |  h = VIDEO
```

VOIP and P2P are the best classes, with very few false positives. In the case of VOIP, the most common error is to label as BROWSING a VOIP sample, which makes sense, some of the applications used for capturing VOIP are web based, therefore they will also generate some browsing traffic. In the case of P2P we have almost a perfect match. AUDIO and VIDEO have a similar pattern, being most confused with BROWSING, and viceversa. Again, this confusion makes sense, all video applications used are web based.

If we look at the BROWSING column, which shows how many classes have been wrongly labelled as BROWSING, we can see that it is the most common mistake. At the same time, the AUDIO, VIDEO and CHAT are the most common mistakes when labelling BROWSING traffic, i.e. we label as BROWSING a sample that belongs to CHAT, AUDIO or VIDEO. Since many applications are web-based or use https as communication protocol it is normal that the BROWSING class becomes the most common mistake. Moreover, as we explain in Section 3, we label all flows generated from the class X .pcap file as X, which means that our dataset will have some background noise that may difficult the detection of certain types of traffic, like BROWSING which may be present in all samples with independence of the label.

6 CONCLUSIONS

In this paper we presented a time analysis to detect and characterize Tor traffic. The set of features chosen are time-based statistics only (-fiat, -biat, -flowiat, -idle, -active and -psec) derived from the observation of traffic flows between a Tor client and a Tor entry node. The results obtained prove that time base features can be used to detect Tor traffic efficiently: only 10 features are needed. Moreover, time base features can be used to characterize Tor traffic and efficiently detect different traffic applications like VoIP, Audio Streaming, P2P, File-Transfer and Video Streaming. In addition to the Tor detection and classification contributions, our results show that flow timeout has an influence on the efficiency of the solution our classifiers perform better when the flows are generated using shorter timeout values, with 15s. as the optimal value, which contradicts the common assumption of using 600s as timeout duration. As part of this work, we published the labelled dataset used in this experiment and the tool used to generate it, so that other researchers can use them to replicate this experiment and to test their own proposals in future. As future work we plan to extend our dataset and further study the application of time-based features to characterize encrypted traffic. Also, we planned to extend our ISCXFlowMeter application to extract the other features such as Flow-based and Packet-based to experiment the combination of these feature sets.

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