Analyzing HTTPS Traffic for a Robust Identification of Operating System, Browser and Application

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***Abstract*—Desktops and laptops can be maliciously exploited to violate privacy. There are two main types of attack scenarios: active and passive. In this paper, we consider the passive scenario where the adversary does not interact actively with the device, but he is able to eavesdrop on the network traffic of the device from the network side. Most of the Internet traffic is encrypted and thus passive attacks are challenging. In this paper, we show that an external attacker can robustly identify the operating system, browser and application of HTTP encrypted traffic (HTTPS). We provide a large dataset of more than 20,000 examples for this task. We present a comprehensive evaluation of traffic features including new ones and machine learning algorithms. We run a comprehensive set of experiments, which shows that our classification accuracy is 96.06%. Due to the adaptive nature of the problem, we also investigate the robustness and resilience to changes of features due to different network conditions (e.g., VPN) at test time and the effect of small training set on the accuracy. We show that our proposed solution is robust to these changes.**

***Index Terms*—Encrypted Traffic, HTTPS, Operating System, Browser, Application**

I. Introduction

There are two main types of attack scenarios: active and passive. Active adversaries try to physically or remotely control the user device. Passive adversaries may violate the privacy of the user by sniffing the network traffic of the devices from the network side. In this work, we consider passive attacks.

If network traffic is not encrypted, the task of a passive attacker is simple: he can analyze the payload and read the content of each packet. User activities tracking on the web was proposed in [1]–[4]. This has been done by analyzing unencrypted HTTP requests and responses. A passive adversary may use this information for understanding user actions and revealing information regarding personal interests and habits.

However, most of the Internet traffic today is encrypted. This happens both as users start to gain more familiarity with privacy threats and as Google encourages all website owners to switch from HTTP to HTTPS by taking into account whether sites use secure, encrypted connections, as a signal in their ranking algorithms [5], [6]. As a result, traditional Deep Packet Inspection (DPI) methods for information retrieval are not viable.

Many works have shown that encryption is not sufficient to protect confidentiality [7]–[46]. Bujlow et al. [30] presented a survey about popular DPI tools for traffic classification. Nguyen and Armitage [31] survey machine learning techniques for Internet traffic classification. Moore et al. [36] used a Naïve Bayes classifier which is a supervised machine learning approach to classify Internet traffic applications. Williams et al. [38] conducted a comparison of five machine learning algorithms that were used to classify Internet traffic applications. Auld et al. [37] proposed to use a supervised Bayesian neural network to classify Internet traffic applications. Alshamarri et al. [39] compared AdaBoost, Support Vector Machines, Naïve Bayes, RIPPER and C4.5 in order to classify Skype traffic. Donato et al. [42] presented a method for application classification called the Traffic Identification Engine. Niemczyk et al. [41] suggested to divide the session to time buckets (10 seconds). The features that were used for each bucket are packet size counts and the time differences between packets. They found the recognition rate of Skype was almost perfect. However, their method was not able to differentiate between browsers and between joint application and browser usage.

In this paper, our threat model focus on passive attacker who targeting a specific user. In this case, the attacker is tries to choose the best vector attack against the user. Therefore, an adversary can surreptitiously monitor the victims network traffic to identify what are the operating system, browser and apps of the user. Based on the vulnerabilities of the tuple, this will let the attacker to choose the relevant malwares or Advanced Persistent Threat (APT) method. The attacker can either sniff the wireless network of the user or can sniff the user traffic over the ISP network (e.g. government). However, due to the encryption the attacker may consider to use machine learning to classify the user operating system, browser and applications.

Our paper shows that using machine learning with network traffic analysis can be used to infer private information about the user computer, i.e., OS, Browser, Application, even though the traffic is encrypted. Our preliminary research [47] was the first to propose a robust solution for operating system, browser and application via encrypted traffic analysis.

Our paper's main contributions are:

- This is the first work that shows how to identify the user's operating system, browser and application from his HTTPS traffic. Inspired by other works presented above, we exploit traffic patterns. Additionally, we present new features that exploit browsers' bursty behavior and SSL behavior. Using the baseline features, the accuracy is

93.51% , while using a combination of baseline and new features achieves accuracy of 96.06%.
- We provide a comprehensive dataset that contains more than 20,000 labeled sessions. The operating systems in the dataset are: Windows, Linux-Ubuntu and OSX. The browsers are: Chrome, Internet Explorer, Firefox and Safari. The applications are: YouTube, Facebook and Twitter. The dataset is available for download at [48].
- We show that using small training datasets is possible. For example, using only 500 examples for training (vs. the full training dataset of 0.7×20000) we also reach a reasonable accuracy of 80% for the baseline features and 85% when the new features are added.
- We investigate the robustness of the system to changes of features due to different network conditions. We show that our solution is robust to VPN and changes in cipher suites, where both changes are *only* on the testing data.
- We investigate the resilience of the system to small session time. For example, using only the first 10 seconds of a session for training and testing. We show that although we use shorter sessions which leads to less meta data, we reach a reasonable accuracy of 94.2%.

In this paper, we extend our previous work [47] by adding two machine learning algorithms, investigating the robustness and resilience of our system and adding possible countermeasures and limitations discussion.

The remainder of this paper is organized as follows. In section II we revise the state of the art around our research topic. Section III presents our solution for identifying the user's Operating System, Browser and Application. In section IV we present a through evaluation of our method including its robustness to changes in network conditions at test time. In Section V we discuss limitations and possible countermeasures. Finally, we conclude and discuss future lines of work in Section VI.

II. Related Works

Feature extraction methods for traffic classification include session duration [39], number of packets in a session [35], [49], minimum, maximum and average values of inter-arrival packets time [35], [39], payload size information [35], bit rate [50], [51], round-trip time [50], packet direction [52], SSL parameters [46] and server sent bit-rate [53] that has the advantage of overcoming communication problems such as packet loss and retransmissions.

Liberatore and Levine [54] showed the effectiveness of two traffic analysis techniques for the identification of encrypted HTTP streams. One is based on a naïve Bayes classifier and one on the Jaccards coefficient similarity measure. They also proposed several methods for actively countering the techniques. They found these methods to be effective, albeit at the cost of a significant increase in the size of the traffic stream. Panchenko et al. [55] showed that a Support Vector Machine (SVM) classifier is able to correctly identify web pages, even when the user used both encryption and anonymization networks such as Tor [56]. Cai et al. [57] presented a web page fingerprinting attack and showed that it is able to overcome defenses such as the application-level defenses HTTPOS [58] and randomized pipelining over Tor.

Exploiting traffic features for gaining information has been applied not only with the HTTP protocol but also with other protocols. For example, Song et al. [11] showed that some SSH variants are not secure. They showed that simple statistical analysis was able to reveal sensitive information such as login passwords. Additionally, they showed that advanced statistical analysis on timing information can reveal what users type. Another example of a protocol that was shown to be vulnerable is Voice Over IP (VoIP). Wright et al. [17] showed that it is possible to identify spoken phrases by using encrypted VoIP packet length, when variable bit rate (VBR) encoding is used. They used a Hidden Markov model that achieved more than 90% recall and precision.

Gathering information about the Operating System (OS) or the browser of the user can be useful too. Passive sniffing the OS fingerprinting techniques were proposed in [59]–[61]. Husak et al. [62] proposed real-time exact pattern matching for identification of OS or browser of the user based SSL/TLS fingerprinting. In this work, the system has to identify the SSL parameters and are not robust to changes in the SSL parameters such as cipher suite parameters.

Mobile devices, which have different operating systems and different application implementation which lead in many cases to different network behavior, are also a way to gain information about the user privacy, applications [63]–[69] and actions [8], [70], [71]. Saltaformaggio et al. [70] presented NetScope, passive framework for identifying user activities within the wireless network traffic based on inspecting IP headers. Conti et al. [7], [8], [71] presented high accuracy classification frameworks for various user mobile actions and applications using network features such as size, direction (incoming/outgoing), and timing.

III. Identification of User's Operating System, Browser and Application

The goal of this paper is to identify user operating system, browser and application. To achieve this goal, we use supervised machine learning techniques. Supervised machine learning techniques learn a function that given a sample returns a label. The learning is carried out using a dataset of labeled samples. In our case, we chose to use sessions as samples where a session is the tuple <Protocol, IP source, IP destination, Port source, Port destination> and the label is the tuple <OS, Browser, Application>. Thus, our task is inherently a multiclass learning with 30 classes (see Figure 1a for the labels and their statistics in the dataset).

The rest of this section is organized as follows: In section III-A we describe how we collected the dataset and the dataset characteristics. In section III-B we describe and discuss our feature extraction scheme. Finally, in section III-C we describe the machine learning methodology we used.

A. Dataset

We used the Selenium web automation tool [72] to develop crawlers for gathering the dataset. We gathered all the traffic that passed through port 443 (TLS/SSL). Finally, we split the traffic into sessions using SplitCap [73].

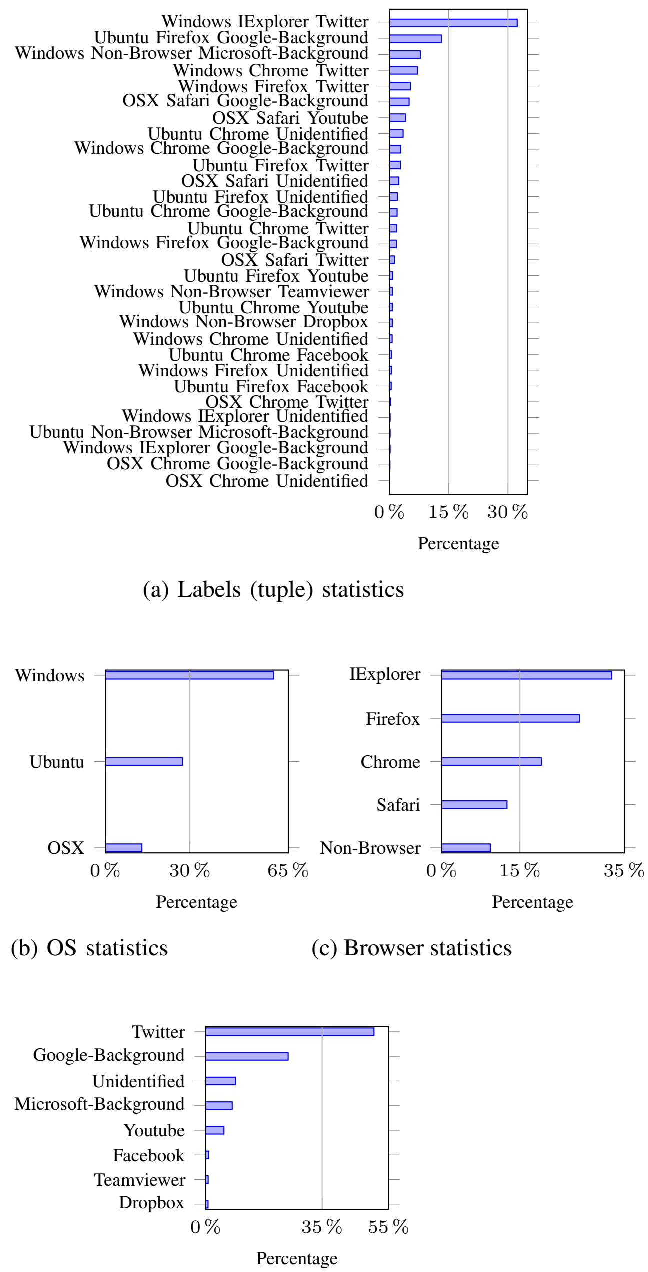
We used the crawlers on a standard Internet connection over various operating systems and various browsers and combinations thereof. For Facebook, the same account was used both for sending and receiving posts. For Twitter, we had one sending account and several receiving accounts (followers) where they ranged over various operating systems and various browsers and combinations thereof. Teamviewer's traffic was generated by us actively without a crawler.

In addition to our active traffic, we also observed background traffic that operating systems, browsers and applications created (Google-Services, Microsoft-Services). Note that, example for services can be Google Analytics or Microsoft Live. Dropbox traffic was composed both of active (no crawler) and background traffic.

Any traffic that we could not identify was labeled as unidentified. The browser label part of the tuple of stand alone applications which do not work under a browser (*e.g.* Dropbox, Teamviewer) were labeled as Non-Browser.

The dataset was collected over the period of more than two months in our research lab over diverse connections (wired and WiFi) and networks conditions (over workdays and weekends 24/7).

Our dataset contains more than $20,000$ sessions. The average duration of a session is 518 seconds where in average each session has 520 forward packets (average forward traffic size is 261 Kbytes) and 637 backward packets (average backward traffic size is 615 Kbytes). The tuple labels statistics can be seen in Figure 1a. Operating system, browser, application statistics can be seen in Figures 1b,1c,1d correspondingly.



(a) Labels (tuple) statistics

(b) OS statistics

(c) Browser statistics

(d) Application statistics

Fig. 1: Dataset statistics

B. Feature Extraction

Using raw data in a machine learning method is problematic as it is non-structured and contains redundant information. Thus, there is a need to build a structured representation of the raw data that is informative to the specific problem domain. Building this representation is called feature extraction [74, Chapter 5.3].

We extract features from a session of encrypted traffic which generally relies on SSL/TLS for secure communication. These protocols are built on top of the TCP/IP suite. The TCP layer receives encrypted data from the above layer and divides data into chunks if the packets exceed the Maximum Segment Size (MSS). Then, for each chunk it adds a TCP header creating a TCP segment. Each TCP segment is encapsulated into an Internet Protocol (IP) datagram. As TCP packets do not include a session identifier, we identify a session using the tuple $<$Protocol, IP source, IP destination, Port source, Port destination$>$.

A session contains two flows: forward and backward. A flow is defined as time ordered sequence of TCP packets during a single TCP session. The forward flow is defined as a time series bytes transported by incoming packets only, while the backward flow is defined as a time series bytes transported by outgoing packets only. We use the forward, backward and their combination as a representation of a connection. Additionally, we also use time series features such as inter arrival time differentials between different packets on the same flow. Based on our previous work [75] for classifying video titles, we also used the bursty behavior of the browsers (peaks) which is defined as a section of traffic where there is silence before and after. An example of the bursty behavior of browsers is depicted in Figure 2. Note that the bursty behavior of browser traffic was also observed for YouTube traffic in [76], [77].

The feature extraction takes as an input the session network traffic and extracts features from it. In this paper, we consider nine sets of features and their combination as can be seen in Table II.

Forward packets
Forward total bytes
Min forward inter arrival time difference
Max forward inter arrival time difference
Mean forward inter arrival time difference
STD forward inter arrival time difference
Mean forward packets
STD forward packets
Backward packets
Backward total bytes
Min backward inter arrival time difference
Max backward inter arrival time difference
Mean backward inter arrival time difference
STD backward inter arrival time difference
Mean backward packets
STD backward packets
Mean forward TTL value
Minimum forward packet
Minimum backward packet
Maximum forward packet
Maximum backward packet
Total packets
Minimum packet size
Maximum packet size
Mean packet size
Packet size variance

(a) common features

TCP initial window size
TCP window scaling factor
SSL compression methods
SSL extension count
SSL chiper methods
SSL session ID len
Forward peak MAX throughput
Mean throughput of backward peaks
Max throughput of backward peaks
Backward min peak throughput
Backward STD peak throughput
Forward number of bursts
Backward number of bursts
Forward min peak throughput
Mean throughput of forward peaks
Forward STD peak throughput
Mean backward peak inter arrival time diff
Minimum backward peak inter arrival time diff
Maximum backward peak inter arrival time diff
STD backward peak inter arrival time diff
Mean forward peak inter arrival time diff
Minimum forward peak inter arrival time diff
Maximum forward peak inter arrival time diff
STD forward peak inter arrival time diff
Keep alive packets
TCP Maxiumu Segment Size
Forward SSL Version

(b) new features

TABLE I: The common features which are features that are used in many traffic classification methods and the new features which are proposed in this paper.

Common Feature Set	a typical feature set (presented in Table Ia), used in many traffic classification methods [36]–[41], [61]
Peaks Feature Set	Only the bursty behavior of the browsers
New Feature Set	A new set of features (presented in Table Ib), based on a comprehensive network traffic analysis, in which we tried to identify traffic parameters that differentiate between different operating systems and browsers. The set of features include new SSL features, new TCP features and the bursty behavior of the browsers (peaks) which is defined as a section of traffic where there is silence before and after.
Common Stats Feature Set	Only statistics parameters from Table Ia
Statistics	Only statistics parameters from Tables Ia, Ib
Combined Feature Set	All available features combined (all the sets above)
Combined no peaks Feature Set	All available features combined minus the peak features
Combined no SSL Feature Set	All available features combined minus SSL related features
Combined no TCP Feature Set	All available features combined minus TCP protocol related features

TABLE II: Feature Sets

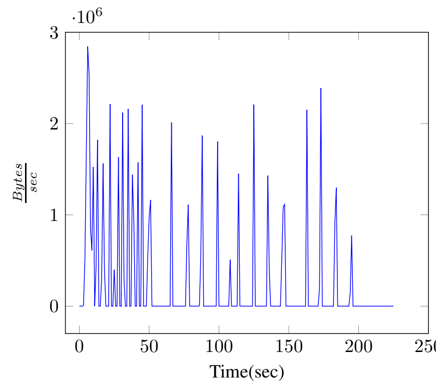


Fig. 2: An example of the bursty behavior of browser traffic.

C. Learning

In this section we describe our machine learning methodology. Supervised classification learning methods learn a classification function from a set of pre-labeled examples. The classification function is then used for classifying unseen test examples. There are two types of supervised classification learning methods. Lazy learning algorithms store the training data as is and then apply a classification function on a new test example where the classification function is parameterized with the pre-labeled training examples. Eager learning algorithms, on the other hand, carry out a learning process on the pre-labeled training examples. Eager learning algorithms often perform better as the offline learning stage increases robustness to noise.

The lazy machine learning algorithm we adapt is the nearest neighbor algorithm [78]. In this algorithm, the classification function computes similarities between a new test sample to all pre-labeled examples. The test sample is then assigned to the class of the most similar example from the training data.

The first eager machine learning algorithm we adapt is the Support Vector Machine (SVM) [79]. A binary linear SVM models training examples as points in space, and then divides the space using a hyperplane to give the best separation among the two classes. We used the LIBSVM package [80] which uses the one-vs-one multiclass scheme. We used three versions of the SVM:

- SVM+RBF - SVM with Radial Basis Function (RBF) as the kernel function.
- SVM+SIM - SVM with threshold similarities to training

samples as features [81]. Similarity is bounded by a threshold. This is a heuristic based on the assumption that dissimilar samples add noise rather than information. The threshold similarity value and the distance function are part of the cross-validation process.

$$u, v \in samples, 1 - \frac{min(distance(u, v), threshold)}{threshold}$$

- SVM+MAP - SVM with modified RBF similarities as features [81] where the similarity is the same as in the RBF function except for the distance function which is not necessarily squared euclidean. The distance function and gamma value are part of the cross-validation process.

$$u, v \in samples, exp(-\gamma \cdot distance(u, v))$$

Our second eager machine learning algorithm we adapt is the Random Forest algorithm [82], [83]. The Random Forest algorithm grows multiple trees by randomly selecting subsets of features. That is, trees are constructed in random subspaces [82], [83].

Therefore, we have five machine learning algorithms. We fine-tune the hyper-parameters of our machine learning algorithms through grid search procedure combined with 5-fold cross validation over the training set. For all machine learning algorithms, features were scaled between zero and one at training and the same scaling factors were used for the test set.

For the KNN algorithm, we used cross validation for choosing both the number of neighbors over the set $\{4, 6, \ldots, 20\}$, uniform or distance-based weights and the distance measures: Euclidean, Manhattan, Chebyshev, Hamming and Canberra. For the SVM algorithm, we used cross validation for choosing both the regularization parameter of SVM, C, over the set $\{2^{-5}, 2^{-3}, \ldots, 2^{15}\}$ and for the gamma parameter of RBF, over the set $\{2^{-15}, 2^{-13}, \ldots, 2^{3}\}$. We used LIBSVM [80] to train and test our dataset. For the Random Forest algorithm we used cross validation for choosing the number of trees over the set $\{20, 40, \ldots, 120\}$.

IV. Results

We trained and tested on 70% train and 30% test splits five times and accuracy is reported as the average of these experiments. We first show that the accuracy of the tuple and its elements (Os, Browser, Application) is high. Then, we wanted show the robustness of our system, by taking samples (training and test) limited by time (the first x seconds/minutes of the sessions). Afterward, we show that the training and testing time is low (test time of millisecond).

In order to show resilience of the system, we show that even when the training set is small we achieve high accuracy and even if we use Virtual Private Network (VPN) or change the cipher suite of the browser, our system still achieves high accuracy.

The accuracy for the tuple $<$OS, Browser, Application$>$ classification with the nine feature sets is presented in Figure 3. There are three main observations: First, the tuple $<$OS, Browser, Application$>$ classification of encrypted classification is possible with high accuracy. Second, using our new features the results are comparable. Finally, in all experiments, using our base + new features achieved the best results where the Random Forest algorithm and SVM+MAP both achieved the highest accuracy.

For tuple classification, the addition of our new features increased accuracy from 93.52% to 96.06%. Confusion matrix for the tuple accuracy is shown in Fig 4. As above, it can be seen that the classification is almost perfect where most of the mistakes are due to the unidentified label which can actually be a correct answer that we could not verify.

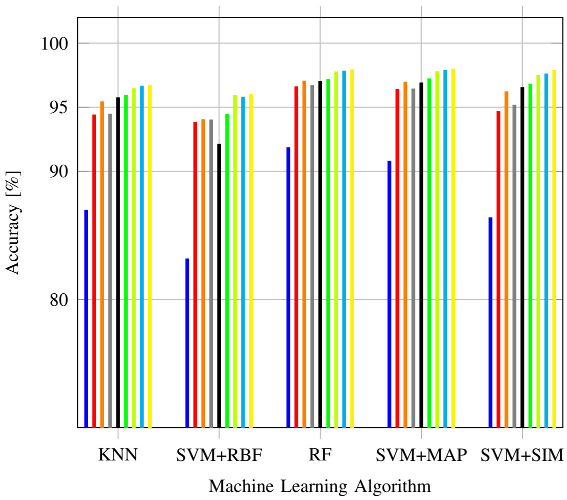
We wanted to investigate if our system achieve high accuracy in case of limited session time which means less data in each session. Therefore, in the next experiments we built training and test set from our session using up to X seconds/minutes (1 second, 10 seconds, 1 minutes, 10 minutes). From Figure 5 we can see that the accuracy decreased but it still high (close to 94%). Moreover, it is interesting to see that the influence of shorting the session decrease after 1 minutes of session, where the results of 1 minutes are close to the accuracy of 1 second.

After understanding that using short sessions does not have high effect on the results, we wanted to investigate the running time of the training and testing. From Figure 6, we can see that the training time of our algorithms is between 10 seconds (RF) to 300 seconds (SVM) while the running time of the testing is less than 1 seconds which means that our testing algorithms can run on real time networks, as the streaming running time is much higher.

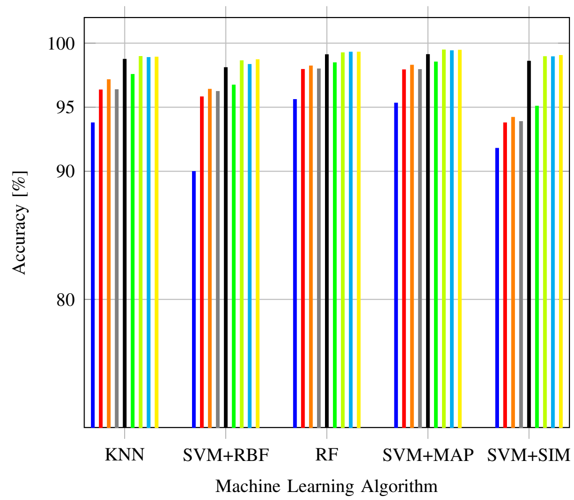
We wanted to see what is the influence of the training data set size. Therefore, we ran an experiment with various training set size (between 50 samples to full data set, 14,443 = 0.7$\times$ 20,000 samples). From Figure 7, we can see that although the training set had less samples, the system still reach a reasonable accuracy of 80% for the baseline features and 85% when the new features were added.

We discuss the effectiveness of our system against adversarial opponents [84]. In this case, the opponent (maybe a user who wants to protect his privacy or an attacker who wants to avoid governments monitoring) will try to cause machine learning to fail by changing the network traffic (e.g. using VPN) or the protocols parameters (e.g. using different set of cipher suites). Note that, the opponent may change his traffic while testing time and not in training. The influence of using VPN can be seen in Figure 8. Although the opponent aggregate all the sessions together, our system is still able to classified in good accuracy (81%) the operation system and the browser. From the figure, we can see that the OS classification has better performance than Browser and OS+Browser where the peaks set gets very low results (30% accuracy). Classifying only the browser, we achieved best performance using SVM+MAP or SVM+SIM with Combined no peaks feature set. Most other combinations have relatively low performance. Classifying both OS and Browser, the best performance is achieved using the SVM+MAP with combined as the set. Most other combinations have relatively low performance.

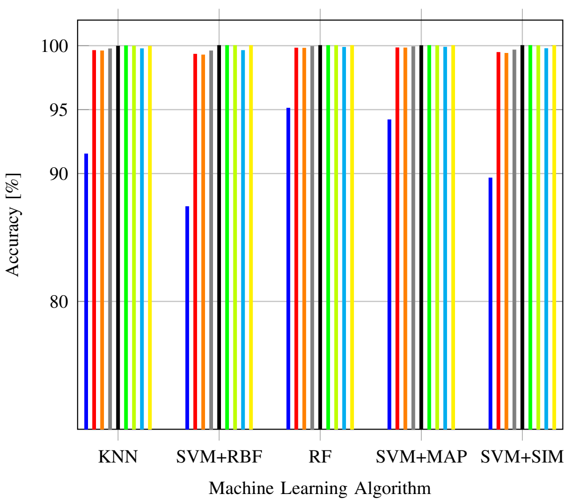
Fig. 9 showed the influence on the accuracy of an attacker that change the cipher suites (SSL parameter). Although the opponent change in the SSL header the number and the vlaue



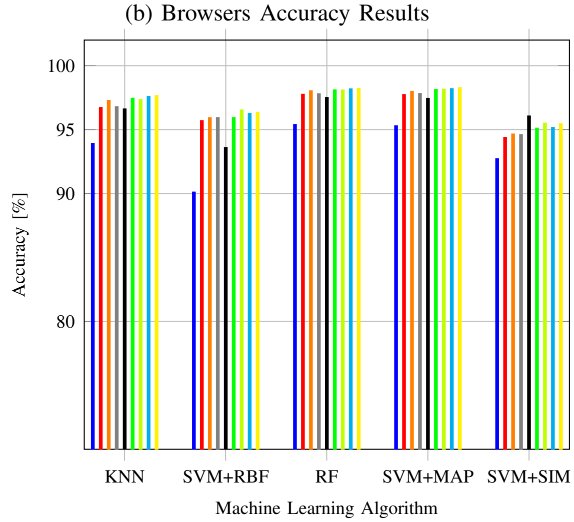
(a) Tuple Accuracy Results



(b) Browsers Accuracy Results



(c) OS Accuracy Results



(d) Applications Accuracy Results

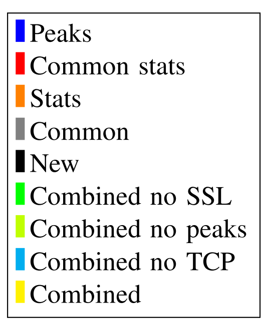


Fig. 3: Accuracy results for KNN, SVM-RBF, SVM-MAP, SVM-SIM, RF with different features sets. This work is the first to show that the tuple <OS, Browser, Application> classification is possible with high accuracy. Note that, naive classification based on the data set statistics will have only 32.34% accuracy (by classifying all sessions as <Windows, IExplorer, Twitter>, see Fig. 1). Adding our new features increased the accuracy to 96.6%.

of the cipher suites, our system is still able to classified in good accuracy (91%) the operation system and the browser. From the figure, we can see that the OS classification has better performance than Browser and OS+Browser where the peaks set gets very low results (65% accuracy). Classifying only the browser, we achieved best performance RF with Combined no peaks feature set. Classifying both OS and Browser, the best performance is achieved using the RF with combined as the set.

Predicted labels

Real labels	Windows IExplorer Twitter	Ubuntu Firefox Google-Services	Windows Non-Browser Microsoft-Services	Windows Chrome Twitter	Windows Firefox Twitter	OSX Safari Google-Services	OSX Safari Youtube	Ubuntu Chrome Unidentified	Windows Chrome Google-Services	Ubuntu Firefox Twitter	OSX Safari Unidentified	Ubuntu Firefox Unidentified	Ubuntu Chrome Google-Services	Ubuntu Chrome Twitter	Windows Firefox Google-Services	OSX Safari Twitter	Ubuntu Firefox Youtube	Windows Non-Browser Teamviewer	Ubuntu Chrome Youtube	Windows Non-Browser Dropbox	Windows Chrome Unidentified	Ubuntu Chrome Facebook	Windows Firefox Unidentified	Ubuntu Firefox Facebook	OSX Chrome Twitter	Windows IExplorer Unidentified	Ubuntu Non-Browser Skype	Windows IExplorer Google-Services	OSX Chrome Google-Services	OSX Chrome Unidentified
Windows IExplorer Twitter	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ubuntu Firefox Google-Services	0	.97	0	0	0	0	0	0	0	0	0	0	.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Windows Non-Browser Microsoft-Services	0	0	.99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Windows Chrome Twitter	0	0	0	.99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.01	0	0	0	0	0	0	0	0	0
Windows Firefox Twitter	0	0	0	0	.98	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.02	0	0	0	0	0	0	0
OSX Safari Google-Services	0	0	0	0	0	.92	.04	0	0	0	.02	0	0	0	0	.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OSX Safari Youtube	0	0	0	0	0	.02	.97	.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ubuntu Chrome Unidentified	0	0	0	0	0	0	0	.84	0	0	0	0	.07	.04	0	0	0	0	.01	0	0	.03	0	0	0	0	0	0	0	0
Windows Chrome Google-Services	0	0	.01	.03	0	0	0	0	.94	0	0	0	0	0	.02	0	0	0	0	0	.01	0	0	0	0	0	0	0	0	0
Ubuntu Firefox Twitter	0	0	0	0	0	0	0	0	0	.95	0	.03	0	0	0	0	.01	0	0	0	0	0	0	0	0	0	0	0	0	0
OSX Safari Unidentified	0	0	0	0	0	.06	.01	0	0	0	.91	0	0	0	0	.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ubuntu Firefox Unidentified	0	.02	0	0	0	0	0	0	0	.08	0	.87	0	0	0	0	.01	0	0	0	0	0	0	.03	0	0	0	0	0	0
Ubuntu Chrome Google-Services	0	.07	0	0	0	0	0	.18	0	0	0	0	.73	0	0	0	0	0	.02	0	0	0	0	0	0	0	0	0	0	0
Ubuntu Chrome Twitter	0	.02	0	0	0	0	0	.08	0	0	0	0	.03	.84	0	0	0	0	.01	0	0	.01	0	0	0	0	0	0	0	0
Windows Firefox Google-Services	0	0	0	.01	0	0	0	0	.01	0	0	0	0	0	.97	0	0	0	0	0	0	0	.01	0	0	0	0	0	0	0
OSX Safari Twitter	0	0	0	0	0	0	.06	0	0	0	.03	0	0	0	0	.91	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ubuntu Firefox Youtube	0	.02	0	0	0	0	0	0	0	.02	0	.02	0	0	0	0	.93	0	0	0	0	0	0	0	0	0	0	0	0	0
Windows Non-Browser Teamviewer	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Ubuntu Chrome Youtube	0	0	0	0	0	0	0	.07	0	0	0	0	.13	.04	0	0	0	0	.74	0	0	.02	0	0	0	0	0	0	0	0
Windows Non-Browser Dropbox	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Windows Chrome Unidentified	0	0	.02	.09	0	0	0	0	.02	0	0	0	0	0	0	0	0	0	0	0	.86	0	0	0	0	0	0	0	0	0
Ubuntu Chrome Facebook	0	0	0	0	0	0	0	.3	0	0	0	0	.04	0	0	0	0	0	0	0	0	.67	0	0	0	0	0	0	0	0
Windows Firefox Unidentified	0	0	.06	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.94	0	0	0	0	0	0	0
Ubuntu Firefox Facebook	0	.06	0	0	0	0	0	0	0	.11	0	.28	0	0	0	0	0	0	0	0	0	0	0	.56	0	0	0	0	0	0
OSX Chrome Twitter	0	0	0	0	0	0	0	.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.75	0	0	0	.06	.06
Windows IExplorer Unidentified	.71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.29	0	0	0	0
Ubuntu Non-Browser Skype	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Windows IExplorer Google-Services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
OSX Chrome Google-Services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
OSX Chrome Unidentified	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Fig. 4: Confusion matrix (rows are ground truth). For most tuples the classification is almost perfect. Exceptions happens mostly between similar tuples and the Unidentified classes (which can actually be a correct answer that we could not verify). For example, “Ubuntu Chrome Google-Services” is mistakenly classified as “Ubuntu Chrome Unidentified” in 18% of the cases and “Ubuntu Firefox Google-Services” in 7%.

V. Possible Countermeasures and Limitations

Although, users and service providers might believe that if they use the right encryption and authentication mechanisms their communications are secure, there are still limitations. As presented in this paper, it possible to develop classifiers for TLS/SSL encrypted traffic that are able to discriminate between Operating Systems, Browsers and Applications. While it is out of the scope of the paper to investigate all possible countermeasures to the proposed attack, we discuss in the following some related issues.

In the results section, we showed that changing cipher suites and using VPNs as counter measures at test time reduced accuracy, but still our proposed attack was able to identify the information with reasonable accuracy.

Another simple countermeasures are padding techniques which may be effective against traffic analysis approaches. However, it has to be considered that padding countermeasures are already standardized in TLS, explicitly to frustrate attacks on a protocol that are based on analysis of the lengths of exchanged messages [6].The intuition is that the information is not hidden efficiently, and the analysis of these features may still allow analysis.

Based on the results, we strongly believe that it is not trivial to propose effective countermeasures to the attack we showed in this paper. Indeed, it is the intention of the authors to highlight a problem that is becoming even more alarming after the revelation about the mass surveillance programs that are nowadays adopted by governments and nation states.

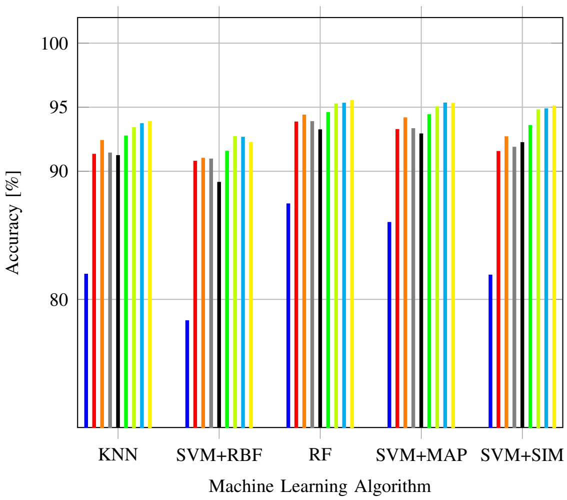
In our opinion, the main limitation of our approach is related to the usage of supervised learning algorithms. It has to be considered that this technique is generally more efficient than the unsupervised learning since it takes advantage of the knowledge of each class of interest. However, it has two main drawbacks: (1) The training dataset has to be labeled with the intervention of a human, (2) It is not possible to recognize classes of events that have not been used during the training phase. (3) Upgrades might change traffic patterns.

We mitigated the first limitation using an automatic approach to label the network traces collected for the training phase. However, the second limitation cannot be addressed without revising the entire approach.

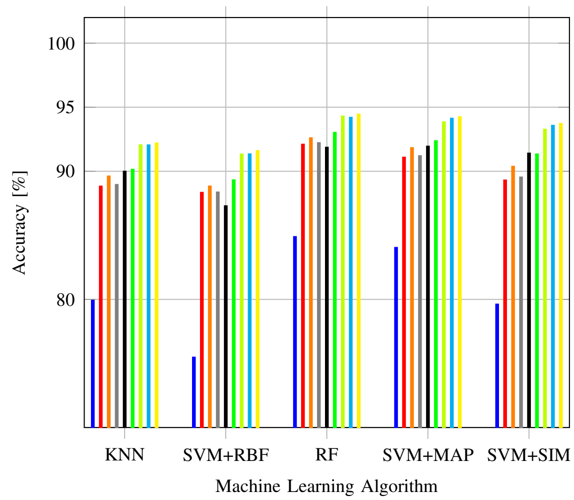
In order to mitigate the third limitation we did the following: (1) We connect our lab to a VPN network which add another layer of encryption (2) We changed the cipher suites number and values of the browsers. In both cases we use the same classifiers where we focus on classifying operating system and browser. From Fig. 8 and Fig. 9 we can see that in both cases there is some effect on the results, however, the accuracy is still high.

VI. Conclusions and Future Work

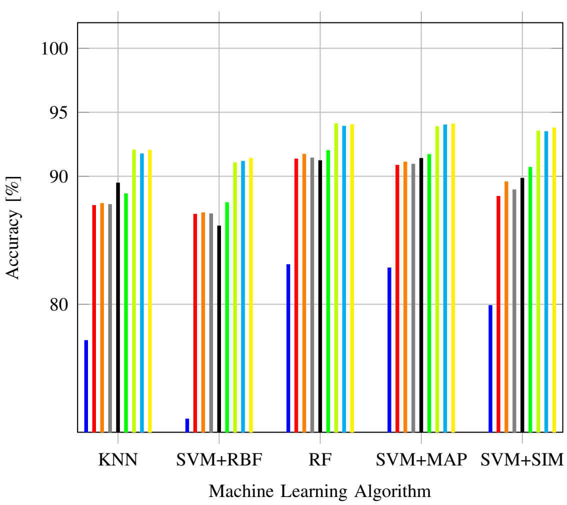
The framework proposed in this paper is able to classify encrypted network traffic and to infer which operating system, browser and application the user is using on his desktop or laptop computer. We showed that despite the use of SSL/TLS, our



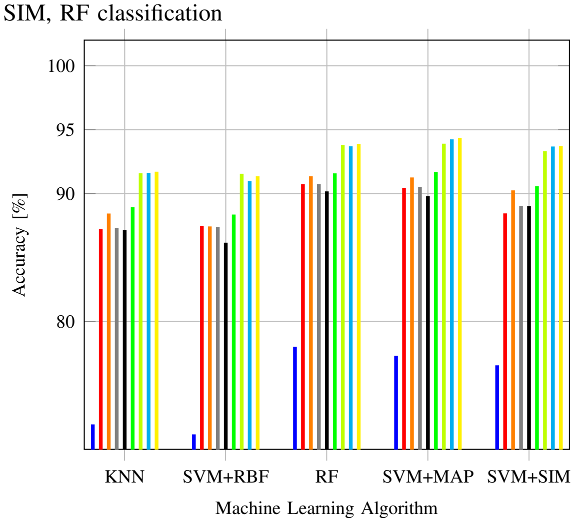
(a) Up to 10 min on KNN, SVM-RBF, SVM-MAP, SVM-SIM, RF classification



(b) Up to 1 min on KNN, SVM-RBF, SVM-MAP, SVM-SIM, RF classification



(c) Up to 10 sec on KNN, SVM-RBF, SVM-MAP, SVM-SIM, RF classification



(d) Up to 1 sec on KNN, SVM-RBF, SVM-MAP, SVM-SIM, RF classification

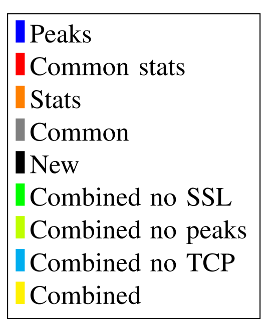


Fig. 5: Real time Tuple classification of a short period of a session (1 seconds, 10 seconds, 1 minute and 10 minutes) using KNN, SVM-RBF, SVM-MAP, SVM-SIM, RF classification algorithms

traffic analysis approach is an effective tool. An eavesdropper can easily leverage the information about the user to fit an optimal attack vector.

A passive adversary may also collect statistics about groups of users for improving their marketing strategy. In addition, an attacker may use tuples statistics for identifying a specific person.

An interesting extension of this work would be to add action classification (*e.g.* send a tweet, receive a post) to the tuple as has been done for application and action for mobile

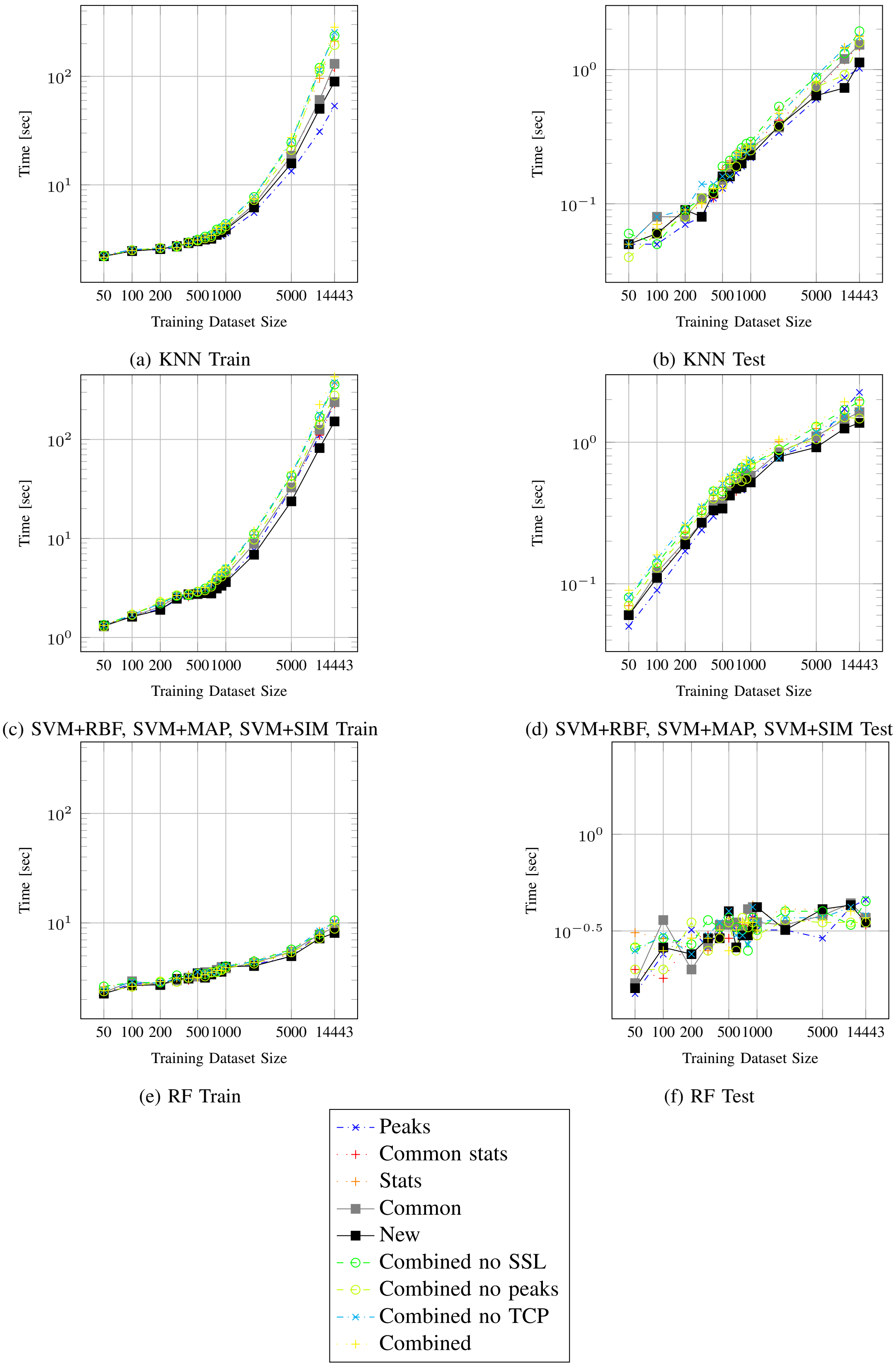


Fig. 6: Training (including cross validation) and testing time of the machine learning algorithms for various training dataset sizes. The x-axis is in logarithmic scale.

devices [8]. Another interesting extension would be to identify operating system and browser also in the mobile world.

Acknowledgment

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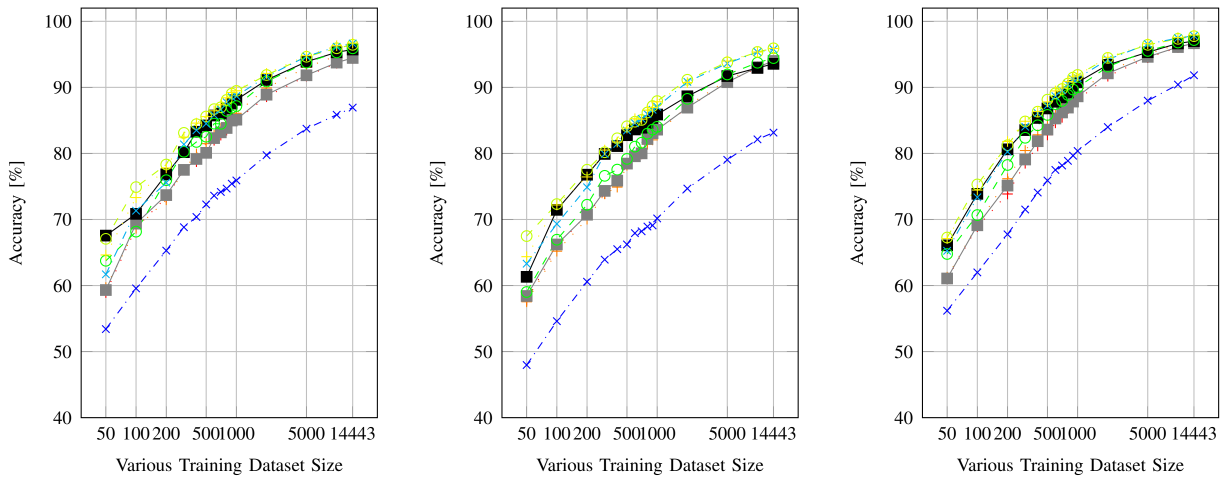

(a) KNN (b) SVM-RBF (c) RF

Fig. 7: Accuracy of KNN, SVM-RBF, RF with various training data set size (Number of Samples). The x-axis is in logarithmic scale.

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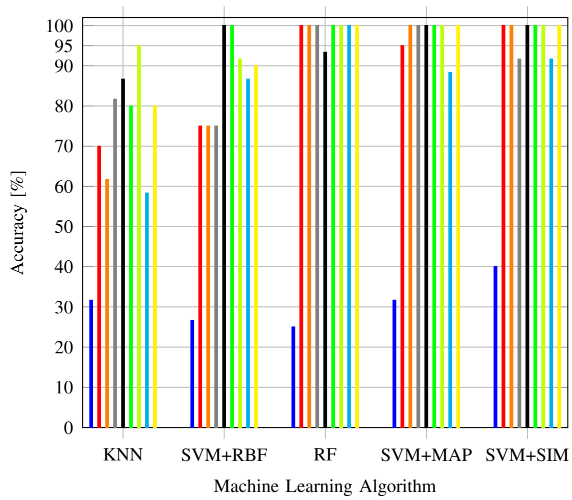
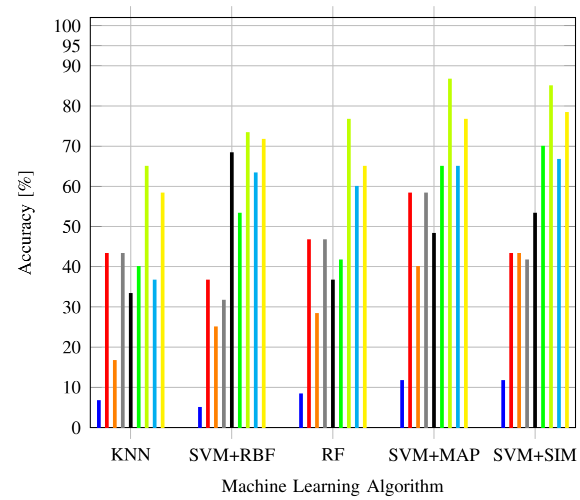
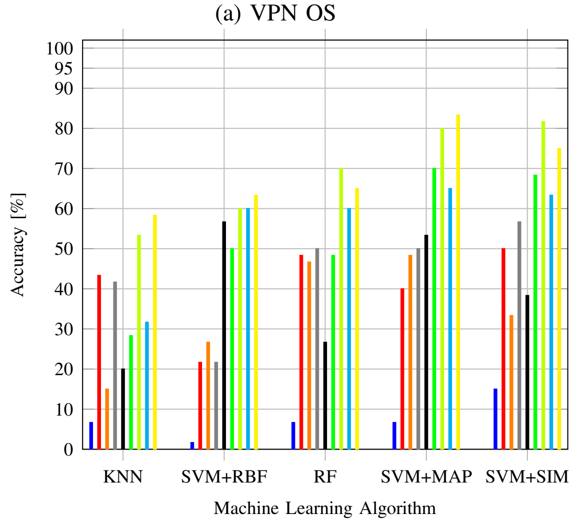


(a) VPN OS



(b) VPN Browser



(c) VPN OS and Browser

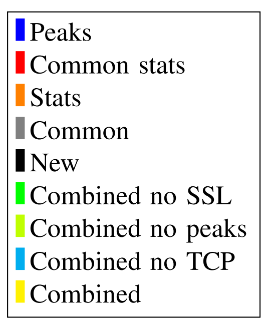


Fig. 8: VPN - The influence of using VPN at test time on the accuracy results

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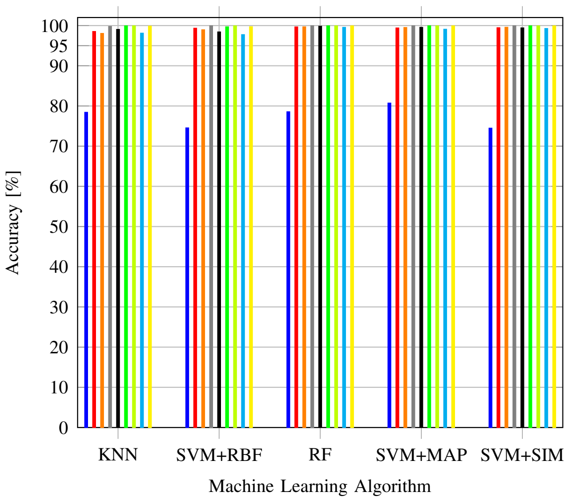
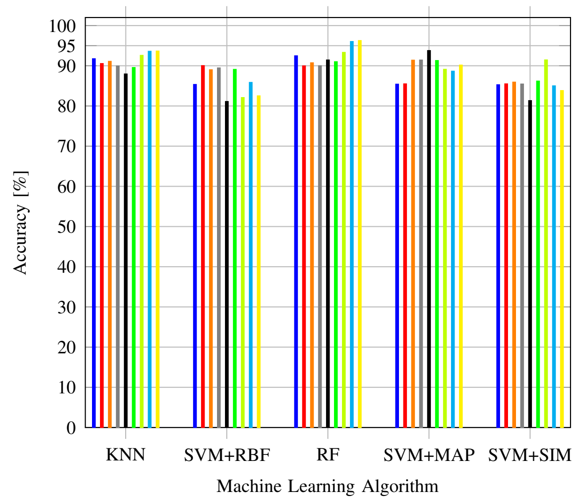
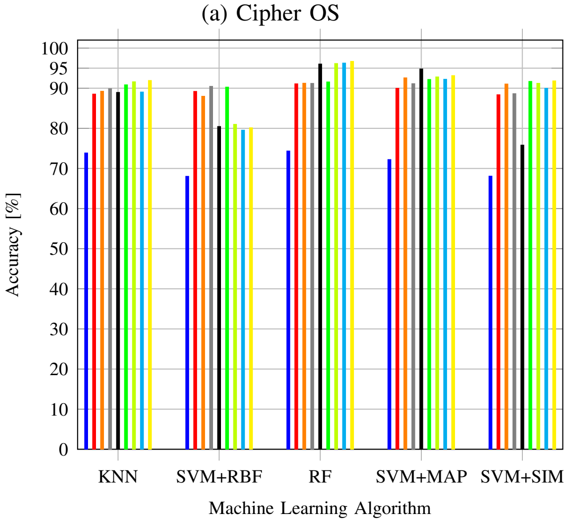


(a) Cipher OS



(b) Cipher Browser



(c) Cipher OS and Browser

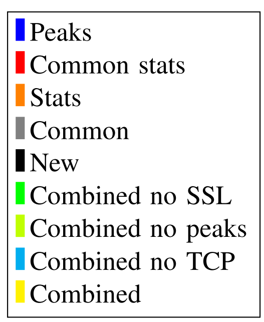


Fig. 9: Cipher - The influence of changing the number and values of the cipher suite at test time on the accuracy results

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