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Automated Behavioral Fingerprinting

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Abstract. This paper addresses the fingerprinting of devices that speak a common, yet unknown to the fingerprinting engine, protocol. We consider a behavioral approach, where the fingerprinting of an unknown protocol is based on detecting and exploiting differences in the observed behavior from two or more devices. Our approach assumes zero knowledge about the syntax and state machine underlying the protocol. The main contribution of this paper consists in a two phased method. The first phase identifies the different message types using an unsupervised support vector clustering algorithm. The second phase is leveraging recent advances in tree support kernel in order to learn and differentiate different implementations of that protocol. The key idea is to represent behavior in terms of trees and learn the distinctive subtrees that are specific to one particular device. Our solution is passive and does not assume active and stimulus triggered behavior templates. We instantiate our solution to the particular case of a VoIP specific protocol (SIP) and validate it using extensive data sets collected on a large size VoIP testbed.

1 Introduction

Over the past few years, there has been an increased effort in the research community towards the automated analysis and reverse engineering of network protocols. The driving forces are multiple and range from practical needs to analyze network traffic generated by malware where the most notorious case is the Storm bot and up to the development of open source implementation for poorly documented protocols, as it was the case of the SMB protocol [1] for example. A related problem is the automated and passive fingerprinting of devices using an unknown protocol. While some research efforts in this direction have been recently made in [2] in order to learn the syntax and grammar that generated the protocol messages, to our knowledge, none until now has addressed the automated learning of the specific behavior of a protocol in order to fingerprint a device or a protocol stack. [3] and [4] are close and complementary works as they aim to learn an unknown protocol to automatically respond to requests. The research challenges that we face are related to learning the relevant protocol operations/primitives and modeling the protocol message sequences such that automated learning is possible. If packet captures from an unknown protocol are given, we aim first to automatically discover the unknown types of messages. We assume furthermore that no learning set with labeled protocol messages exists, that no encryption is used and that no reverse engineering of the application using such a protocol is possible. We also assume that the number of different message types is a-priori unknown.

Reverse engineering of network protocols is clearly related to the security problem since understanding the protocols is a necessary step for detecting protocol misuse. In addition, fingerprinting is a useful task in the security domain. For an attacker, fingeprinting is a prior work for performing efficient attacks. For a network administrator, it is a tool for security assessment and testing.

The two contributions presented in this paper are:

- the automated analysis of protocols with respect to the types of messages exchanged based on unsupervised learning methods. For instance, if we consider a stripped-off ICMP version, an ICMP echo request message has to be answered by an ICMP echo reply message; assuming that a collection of captured messages is available, our approach should automatically discover that several types of messages exist (ICMP echo request and ICMP echo reply). Thus, our technique can be used as an essential preprocessing phase to the automated learning of the protocol related state machine;
- the learning of the device/stack specific behavior that results from reconstructing/reverse engineering a state machine for a device under test. In the previous example of ICMP for instance, it may be possible to detect a specific device by peculiar behavior related features. Although ICMP is a simple protocol, a large and comprehensive research work [5] (using mostly manual and tedious tests) showed that reliable fingerprinting is possible. We address a new and automated research direction that leverages support vector machines and tree kernels for learning structural behavior features of the underlying protocol.

The paper is structured as follows: related work is analyzed in the next section; the SIP protocol that we use as the first application case is described in the third section; the different metrics to classify the messages are presented in section 4. Message types identification methods and results are described in section 5. Section 6 focuses on the behavioral fingerprinting. Finally, the last section concludes the paper and sketches future research directions.

2 Related works

Automatically recognizing the different messages of a protocol without prior knowledge is a challenging task. This is one part of the reverse protocol engineering goals which also aims to clearly infer the syntax and grammar of messages *i.e.*, the different fields. Historically, the first technique available was hand-based analysis of dump files provided by packet sniffing software like tcpdump [6]. Obviously, this technique is tedious, limited and very time consuming. Therefore, new methods appeared. The Protocol Informatics project [7] proposes a solution which uses well known bioinformatics algorithms and techniques based on sequence alignment. Given a set of messages protocols, the program tries to determine both constant and variable fields. Several approaches consider the context semantics *i.e.*, the target computer behavior itself: [2] looks for extracted bytes in the message to rebuild the different fields; [8] is based on the execution trace *i.e.*, system calls; [9] proposes a dynamic binary analysis to identify separators and keywords; [10] introduces a semi-supervised learning method to determine the message fields. Closer to our goal, an approach to cluster the messages captured on the network by types before trying to infer their format is proposed in [11]. To achieve this clustering, the authors propose to tokenize each message *i.e.*, to find the different fields by considering that each binary bytes is a binary token and that each text sequence between two binary bytes is a field. The technique proposed in [12] is also based on identifying the different fields thanks to a delimiter. This is done by instrumenting the protocol application by studying how the program parses the messages. [13] focuses more on the state machine construction of multiple flows protocol. Application dialog replay is a very close domain since its goal is to construct a valid replay dialog by identifying the contents which need to be modified thanks to sequence alignment techniques [3] or by building a model from application inputs and outputs [14]. ScriptGen [4] is another approach which is able to construct the partial state-machine of a protocol based on network traces in order to automatically generate responses to attacker requests sent to a honeypot. Network and service fingerprinting is a common task is security assessment, penetration testing and intrusion detection. The key assumption is that subtle differences due to development choices and/or incomplete specification can trace back the specific device/protocol stack [15]. There are excellent tools that implement such schemes: p0f [16] uses TCP/IP fields to passively identify the signature of a TCP/IP stack, while nmap [17] does actively follow a stimulus-response test in order to detect the operating system and service versioning of a remote device. [18] aims to construct automatically the fingerprints by active probing. The research community has addressed the fingerprinting of SIP devices [19, 20] by automatically constructing message specific fingerprints. In [21] and [22], the goal is a little bit different because the authors aim to correctly identify the flow types *i.e.*, the protocols used. In a previous contribution [23], we have addressed a syntax driven fingerprinting, where parse trees of captured messages were used to learn distinctive features capable to perform fingerprinting. In that study, we assumed that BNF [24] specifications are available and that individual messages can be used to infer vendor/stack specific implementation characteristics. This is different from the current approach where no a-priori knowledge of the syntax is assumed. Secondly, we did not consider until now the behavioral aspects for the fingerprinting task. In this paper we do consider the latter and we leverage differences in induced state machines in order to perform fingerprinting.

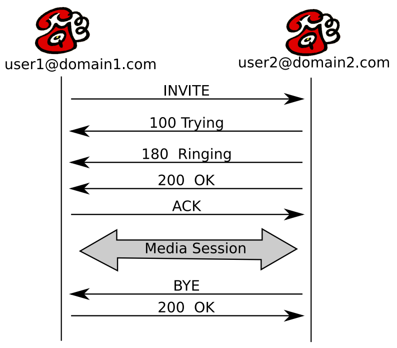


Fig. 1. SIP transaction example

3 Session Initiation Protocol (SIP)

SIP [25] is the de-facto signalisation protocol for the management of VoIP communications. Its main features are related to the establishment, tear-down and negotiation of VoIP sessions and it comprises a rich set of protocol primitives and options as well as a complex underlying state machine. We consider SIP to illustrate our approach for several reasons. Firstly, the number of operations is relatively important (more than 10). Secondly, due to its design, a clear delimitation of transport level information and network level information does not exist, thus making the automated analysis difficult. Thirdly, the distribution of individual message types is quite unbalanced: some message types appear very rarely such that small sided and under-represented classes have to be dealt with. Although a complete overview of SIP is beyond the scope of this paper, a short introduction is given below. SIP messages are divided into two categories: requests and responses. Each request begins with one of the following keywords: `REGISTER, OPTIONS, INVITE,UPDATE, CANCEL, ACK, BYE, SUBSCRIBE, NOTIFY, PRACK, PUBLISH, INFO, REFER, MESSAGE`. The SIP responses begin with a numerical code of 3 digits divided into 6 classes identified by the first digit.

A SIP transaction is illustrated in the figure 1. It is an usual example when *user1@domain1.com* wants to call *user2@domain2.com*. So *user1* initiates the connection by sending an *INVITE* request. First, the callee *user2* informs that it receives the request and will try to achieve its by the *Trying* message. The *Ringing* message means that the user is alerted of the incoming call. When *user2* decides to accept the call, the *OK* response is sent. The caller acknowledges this one and the media session over RTP (Realtime Transport Protocol) [26] is established. Finally, *user2* hangs the phone, a *BYE* message is sent and the other party send an *OK* response to accept the ending of the session. Obviously, many details are omitted like the negotiation of parameters.

We have built a dataset of 1580 SIP messages, generated using several phones coming from different manufacturers. In our traces we minded 27 different kinds

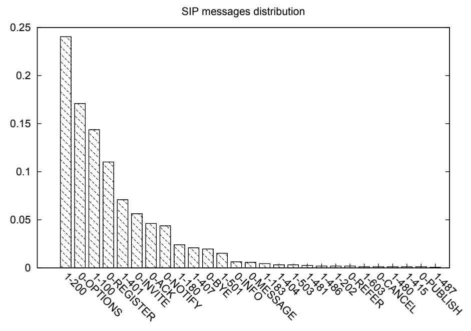


Fig. 2. SIP messages distribution

of message which are the most important and used in VoIP networks. Their empirical distribution is illustrated in figure 2.

Regarding SIP as a target protocol, we would like to be able to automatically identify the 27 types of messages and automatically build tools that can identify abnormal sequences which are not compliant with the protocol, but can be linked to a specific SIP stack and/or vendor. We had to use a known protocol (SIP) in order to be able to assess the accuracy and precision of our approach but it can be generalized towards any protocol. One of the key components is the differentiation among several method types with appropriate metrics.

4 Metrics and distances for protocol messages

Character distribution The character distribution d of a message is based on the statistical distribution of its characters. Intuitively, if two messages m_a and m_b are of the same type, their distributions should be similar. The natural and logical measure is the symmetric relative entropy or Kullback-Leibler divergence:

$$char\_dist(m_a, m_b) = \sum_i d(m_a)_i log(\frac{d(m_a)_i}{d(m_b)_i}) + \sum_i d(m_b)_i log(\frac{d(m_b)_i}{d(m_a)_i}) \quad (1)$$

where i represents all possible characters.

Relative character distribution An alternative character distribution can be constructed to capture the relative character distribution of the message m: *rel_char_dist*. It is based on the distribution of characters but can deal with simple enciphering schemes like for example the per character XOR encryption. It uses an ordered distribution [27] of the character frequencies. Thanks to this metric we have:

$$rel\_char\_dist(m \oplus k) = rel\_char\_dist(m) \forall\ key\ k \quad (2)$$

Character position A third metric that can be associated to each message is the character position. Basically, each message of a protocol has different fields and each message of the same type usually has common field filled with similar content. Therefore, the character at a certain position is often the same for a certain type of message. This metric $char\_pos(m)$ determines the average position of each character of the message m:

$$char\_pos(m)(c) = \frac{\sum_{i=1}^{i=k} pos(a_i)}{k} \tag{3}$$

where i is the index of the character c with k occurrences in the message and $pos()$ the function returning the position of the index of a given character.

Weighted character position Most protocol messages are formed by a header containing the type of the message followed by options, arguments and an additional payload. This comes from good and established protocol design patterns. The $weighted\_char\_pos(m)$ balances more the first characters:

$$\forall \; character \; c \; occurring \; k \; times, \; p_2(m)(c) = \frac{\sum_{i=1}^{i=k} pos(a_i)^{-1}}{k} \tag{4}$$

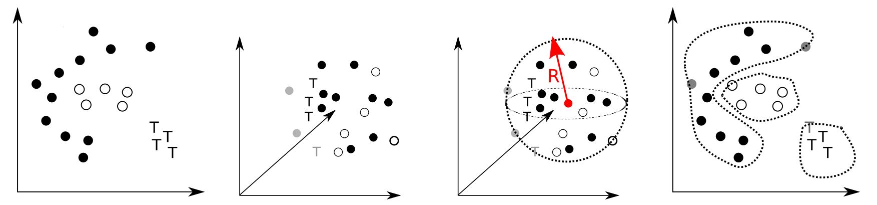
The key assumption is that messages of the same types should start with similar headers even if the message contents are totally different.

5 Automated protocol clustering

Using the previously defined metrics, we derive an unsupervised clustering method that combines two clustering methods in order to determine the number of different messages types. The first technique is a new method relying on unsupervised support vector clustering [28]. The second method is based on the well known agglomerative nearest neighbor method [29]. This last technique considers each data point as an individual cluster. The two clusters with the smallest inter-distance are merged into one. Then, this step is repeated until the smallest inter-distance is higher than a threshold t.

5.1 Support vector clustering

The support vector clustering (SVC) technique has been introduced in [28] and leverages machine learning paradigms based on support vector machines (SVM) [30] techniques. Such techniques show good accuracy with a limited overhead in different domains [31]. The initial data points 3(a) are mapped from the input space to a high dimensional space using a non linear transformation 3(b). The goal is to find the smallest sphere which contains all the points in the high dimensional space 3(c). This sphere is mapped back to the original input space and forms a set of countours which are considered as the cluster boundaries 3(d). The final step determines the cluster of each point by checking which boundaries contain it.



(a) Initial data points (b) Mapping to high dimensional space (c) Looking for the hyper-sphere (d) Hyper-sphere projection in initial dimensions

Fig. 3. SVC example

Consider Φ, a nonlinear transformation and $\{x_i\}$ the set of N points in the original d-dimensional input space. The training phase consists of finding the smallest hyper-sphere containing all the transformed points *i.e.*, $\{\Phi(x_i)\}$ which is characterized by its radius R and its center a. Therefore we have:

$$\|\Phi(x_i) - a\|^2 \leq R^2 \ \forall i \tag{5}$$

The original problem is casted into the Lagrangian form by introducing the lagrangian multipliers (β_i and μ_i) and the penalty term ($C\sum_i \xi_i$):

$$L = R^2 - \sum_i (R^2 + \xi_i - \|\Phi(x_i) - a\|^2)\beta_i - \sum_i \xi_i \mu_i + C \sum_i \xi_i \tag{6}$$

In fact, the ξ terms are slack variables allowing some classification errors. Then, the problem is turned into its Wolfe dual form and the variables a and R are eliminated due to Lagrangian constraints.:

$$W = \sum_i \Phi(x_i)^2 \beta_i - \sum_{i,j} \beta_i \beta_j K(x_i, x_j) \tag{7}$$

where $K(x_i, x_j)$ is typically defined by a Gaussian Kernel:

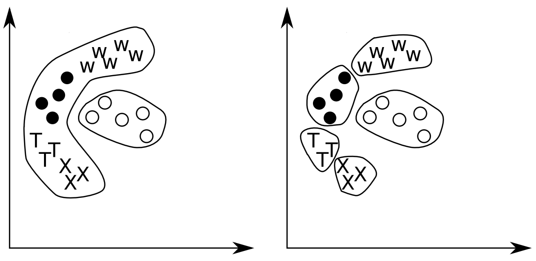
$$K(x_i, x_j) = e^{-q\|x_i - x_j\|^2} \tag{8}$$

where q is another parameter named `Gaussian width`.

Next, a labeling step has to determine the points that belong to the same clusters by a geometric approach. In fact, two points are considered of the same clusters if all the points on the segment between them in the original space are in the hypersphere in the high dimensional feature space.

5.2 Global method

Even if SVC enables the discovery of intertwined clusters, the accuracy can be limited when a single shape comprises different clusters. The figure 4 shows such



(a) SVC clustering (b) Nearest neighbors algorithm

Fig. 4. Global Method

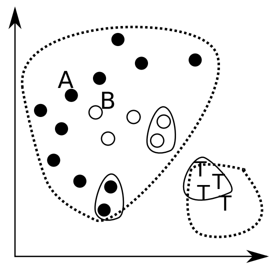


Fig. 5. Limitation of nearest neighbors clustering

a case, where in figure 4(a), the SVC method is able to isolate two large clusters but none the single ones which composes the largest one. These constructed clusters can be furthermore split by an additional nearest neighbors technique for each of them. Hence, this second step is necessary. Obviously, it depends also on the data to classify and our experiments in the next sections show the benefits of the combination of these two methods. Furthermore, several multi-pass clustering methods exist and are introduced in [32]. Complex clusters boundaries are discovered by the SVC technique. By applying the nearest neighbors technique, the result shown in figure 4(b) can be obtained. However, applying only the nearest neighbors technique will entail a bad classification as illustrated in figure 5. Therefore, we propose a global method which consists in two steps:

– a first clustering using SVC
– a second cluster splitting using nearest neighbors technique

5.3 Evaluation metrics

We consider several metrics in order to assess the quality of the clustering method Consider n messages to be classified, $m_1 \dots m_n$, divided into r types and k clusters found: $c_1 \dots c_k$ with $k \leq n$. At the end of the classification, a label is assigned to each cluster which is the predominant type of the messages within. However, only one cluster per type, the largest one, is allowed. If $c(m_i)$ represents the cluster containing m_i then $t(m_i)$ is the real type of the message m_i and $t(c_i)$ is the type assigned to the cluster (c_i).

The first metric is the classification rate cr and represents the ratio of messages which are classified in the right clusters:

$$cr = \frac{\sum_{i|t(m_i)=t(c(m_i))} 1}{n} \tag{9}$$

The second metric is the proportion of different message types which were discovered:

$$cf = \frac{r}{k} \tag{10}$$

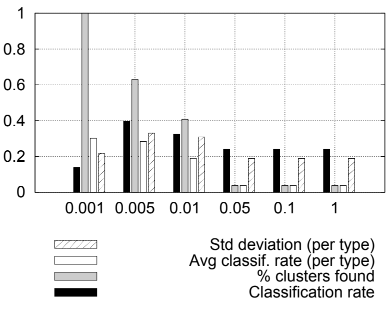
The latter is a rather important metric because performing a good classification rate can be easy by discovering the main types and ignoring unusual ones. In our dataset for instance, having a classification rate close to 100% can be obtained without discovering small clusters like 603, 480, 486, 487 as shown in figure 2. Some of these classes have only one recognized message. The classification rate can also be computed for each type y:

$$cr_{type}(y) = \frac{\sum_{i|t(m_i)=y} x_i}{\sum_{i|t(m_i)=y} 1} \; where \; x_i = 1 \; if \; t(m_i) = t(c(m_i)) \; else \; 0 \tag{11}$$

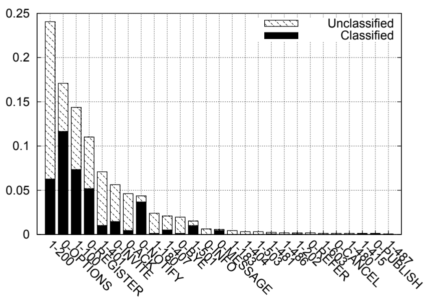
In practice we will consider the average value and the standard deviation by computing this metric for all possible kinds. Therefore, the classification accuracy has to be discussed regarding these different metrics. Because, several figures relate to the accuracy, a common key will be used and will be displayed only in figure 6(a). We analyze the composition of the different clusters with two metrics. The first one is the percentage of good classified messages which are contained in the considered cluster type. The second one is the percentage of messages of this type which are not present in the cluster.

5.4 Nearest neighbors technique results

We consider the first metric to be the relative character distribution. The results are presented on figure 6 where the parameter t varies. This parameter is the maximal distance authorized between two points. The best tradeoff between the classification rate and the number of clusters found is obtained for $t = 0.005$ on the figure 6(a). In this case, about 40% of messages are classified correctly and 60% of the types are found. This shows that for 40% of types the average classification rate is 0% and the standard deviation of the classification rate per type is relatively high. The third bar represents the average classification rate per type which is close to the global classification. The composition of the clusters is interesting since they are similar (see figure 6(b)). In fact, there is no type which is totally well classified. So each cluster contains a relatively high proportion of misclassified messages. t is the main parameter of the nearest neighbors algorithm and does have a high impact on the accuracy (see figure 6(a)). When t increases, less clusters are found because the maximum distance between two points of a cluster is increased and so the cluster sizes are larger. Hence, when t increases, the clusters are merged. The classification rate variation is less obvious: when t increases, it begins by increasing and followed by a decrease. The reason is correlated to the number of clusters. With a small t, the cluster sizes are small too leading messages of the same types to be split into multiple clusters. This entails a bad classification rate because only the biggest one is considered for each kind. When t increases, the clusters are merged, especially many clusters



(a) Accuracy



(b) Clusters details with $t = 0.005$

Fig. 6. Relative character distribution results

of the same kind. Then, clusters of different types can be grouped into one and in this case all messages of one type are missclassified in the new cluster which decreases the classification rate.

The next experiment is based on the character distribution which captures the information in the characters. To limit the effect of the zero values, the results using the smoothing distribution is presented on the figure 7. We checked with other experiments that the smoothing technique has a low impact on the classification rate but allows to discover easily more kinds of message. Comparing the relative character distribution results, they are not significantly improved except for the number of clusters found: about 90% with a classification rate of about 40% ($t = 0.05$). The number of found clusters is better with the same classification rate. This is confirmed by the increase of the average classification rate per type. This means that some small clusters are found too. Moreover, the associated standard deviation is reduced for the same reason.

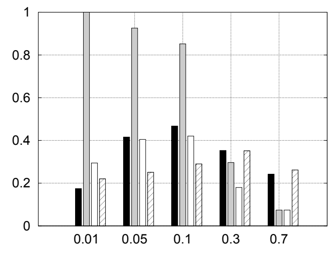
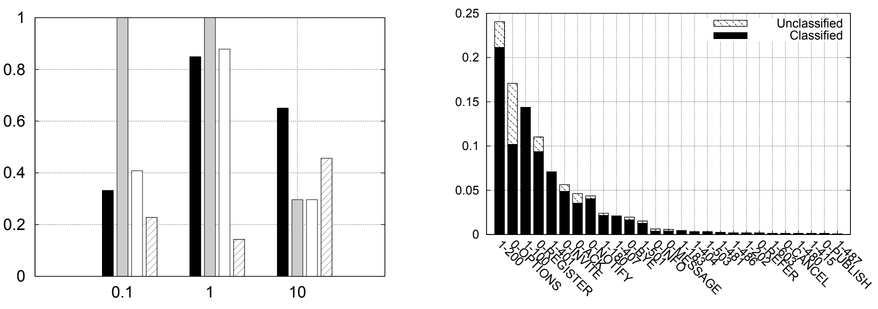


Fig. 7. Smoothing character distribution results - Accuracy

The character position metric is accounting for that the first characters in a message are most probably relevant for the message identification. For instance, the INVITE message has two “I” in the first 7 bytes, and thus a good character-



(a) Accuracy (b) Clusters details with $t = 1$

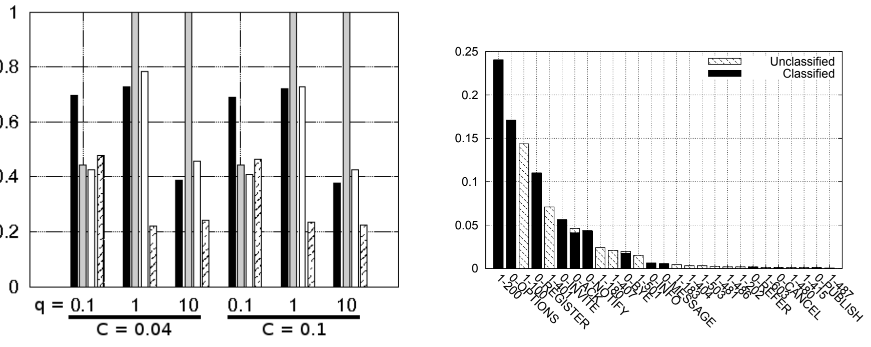
Fig. 8. Weighted characters position results

istic of this message is that this letter is more present at the beginning. However, an INVITE message contains basically a long payload formed with uri, parameters and so on. It may also contain “I” because its length is much higher than the INVITE keyword. The weighted character position metric gives more importance to first characters. The results plotted in figure 8(a) are very good as it is possible to find all the different kinds of message with a global and per type classification rate close to 85%. The details of the classification are illustrated in figure 8(b). In fact, the misclassified messages are shared out within several clusters which entails a small standard deviation for the classification rate per type on figure 8(b). So, increasing the accuracy has not to focus on single or few types of messages only.

5.5 SVC technique results

We applied the SVC method with different values for the Gaussian width q and the penalty factor C. The weighted character position metric is used because it is the best to differentiate the messages. As it is shown in the figure 9(a), the best possible accuracy is 0.73 for the classified messages with all types of messages found. This result is good but slightly lower than the nearest neighbors technique on figure 8 (85% of good classification). This is mainly due to a poor discovery of the smallest clusters because the standard deviation of the specific classification rate per type is higher. When the Gaussian width q increases between 0.1 and 1, the difference between the packets is emphasized in the high dimensional feature space. Hence, the messages clusters are more split and the accuracy is improved. However, when q is too high, the number of clusters continues to increase with redundant types. The number of found clusters is then still good but due to many redundant cluster types, the classification rate drops.

The cluster composition is interesting. In this case, the best accuracy provides clusters similar to the previous obtained in the figure 8 where all kinds of clusters are represented with a little proportion of missclassified messages inside each one. However, if we consider the case of $C = 0.04$ and $q = 0.1$ in figure 9(b)



(a) Accuracy (b) Clusters details with $q = 0.1$

Fig. 9. Weighted characters position SVC results

with a lower accuracy, the clusters are totally different, all types are not found but for most of them, all messages are totally discovered. It means that these clusters represented by black bars contain also messages of other types because the latter ones are not classified in their own clusters -represented by stripes bar (unclassified). We apply the nearest neighbors technique on each cluster to split them. By looking for the best t value, we found $t = 1.1$ which allows to classify 91% of the messages and to discover 96% of the types of the message.

5.6 Other protocols

We have applied also our method to other protocols. We considered only the weighted character position metric because it provided the best results in the previous section. Two well known protocols were tested: SMTP [33] (150 packets and 10 types) and IMAP [34] (289 packets and 24 types). To ease the comparison of results, a classical standardization of the data is done. When the nearest neighbors technique is applied, the classification rates are similar for these protocols -as shown in figure 11 - and less than 50% of the messages are well identified. The number of clusters found is better for SMTP. Moreover, using standardized data helps to choose the parameter t in order to obtain the best classification rate. Then $t = 20$ seems to be a good value to apply the nearest neighbors method with the standardized weighted character position metric.

The SVC method instantiated with the IMAP does not improve the clustering accuracy since in the best case, only 36% of the messages are well classified. Hence, doing the second step with nearest neighbors technique is necessary and allows to obtain 49% of good classification. This is slightly better than the nearest neighbors technique as it was 47% on the figure 11. Obviously, this difference is very low but the number of different types found increases from 62% to 96% with SVC. Therefore, even if the combined method doesn't improve the classification rate, it is able to keep the classification rate stable and at the same time discovering more message types. The figure 10 shows the accuracy of SVC for

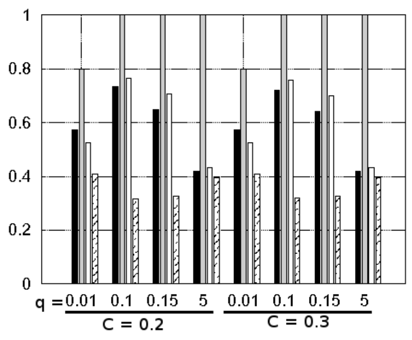


Fig. 10. SVC - SMTP dataset

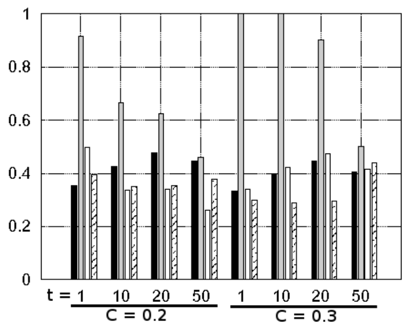


Fig. 11. Nearest neighbors clustering

the SMTP traffic. Since the nearest neighbors technique was able to find most of the types in figure 11, SVC can also find them. Moreover, the classification rate is greatly improved: 72% of messages are correctly identified and 80% of kinds are found. By applying the nearest neighbors technique on the obtained clusters, the results are very close because only one additional type is identified with one packet. Hence, the number of discovered types is 90%. The standard deviation of the classification rate per type is quite high (0.39) principally due to one type totally ignored in both cases.

5.7 Semi automated parameters identification

The assessing of the classification results for a known protocol is easy. The same is much more difficult with unknown because no reference exists. The first conclusion of our study is that the standardized weighted character position metric is the most suitable. For SVC technique, there are two parameters: C and q. In our experiments C has not a great impact as it is highlighted in figure 10. This value is constrained by the SVC technique itself and we have $\beta\_init_i < C < 1$ where β_init_i are initial values of β_i in the Wolfe dual form. These values can be randomly selected since their impacts is only limited to the computation time. Their sum has to be one and we can choose $\beta\_init_i = \beta = 1/\#number\_of\_data\_points$. In our case, the number of data points is the number of packets in the dataset. We can consider a minimal dataset size of 100 and so $C = 0.2$ or $C = 0.3$ are suitable. The parameter q is the Gaussian width and has a real impact on the classification. The aim of the SVC clustering is to obtain large clusters regrouping several types within in. Then, the width of a classification instance is the width of the largest cluster. The width of a cluster is the maximal distance (depending on the metric used) between two points within it. For small values of q, all data points are regrouped into the same cluster and when it increases, they are split. Therefore, when the big clusters will be divided into several ones, if the width is about the same, there will be still a big cluster remaining. If

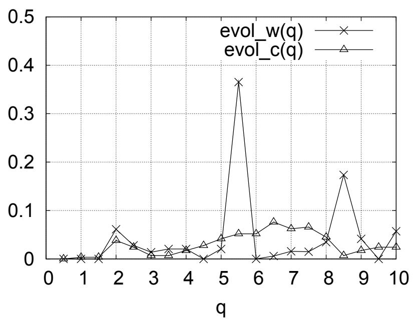


Fig. 12. SVC Gaussian width q selection (IMAP)

the width is different, the cluster has been really divided into several important ones. In the same time, the number of clusters has to increase more during this step. Considering p values of q: $q_1, q_2, \ldots, q_p$, the associated number of clusters $(\#c(q_1), \ldots, \#c(q_p))$ and the classification width $(w(q_1), \ldots, w(q_p))$. To observe the evolutions of these values, we define the following metrics where the division are required to have a value between 0 and 1:

$$evol\_c(q_i) = \frac{|\#c(q_i) - \#c(q_{i-1})|}{max_i(\#c(q_i))} \; if \; i > 1 \; else \; 0 \tag{12}$$

$$evol\_w(q_i) = \frac{|w(q_i) - w(q_{i-1})|}{max_i(w(q_i))} \; if \; i > 1 \; else \; 0 \tag{13}$$

These are plotted in the figure 12 for the IMAP protocol. Several peaks of $evol\_w(q)$ exist, but the last one for $q = 8.5$ can be easily discarded because the number of clusters decreases in the same time. The second one is interesting since it represents the value selected by hand ($q = 5.5$) and the clusters number increases in the same time. This semi automated technique is able to find a good parameter. Finally, the first peak ($q = 2$) is not so high but it concerns simultaneously both metrics. By testing this value, the classification rate is slightly improved by reaching 50%. With others protocols, this approach is able to identify the same optimal parameters which were found by manual testing. Identifying optimal parameters for the nearest neighbors technique can be based on known techniques like [35].

To conclude, combination of weighted normalized position metric and SVC technique is often able to improve the recognition of the messages types. By doing a second phase based on the nearest neighbors technique, the results are always improved.

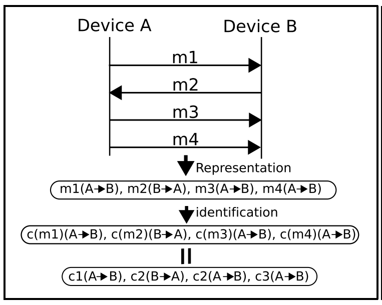

Device A
Device B
m1
m2
m3
m4
Representation
m1(A→B), m2(B→A), m3(A→B), m4(A→B)
identification
c(m1)(A→B), c(m2)(B→A), c(m3)(A→B), c(m4)(A→B)
II
c1(A→B), c2(B→A), c2(A→B), c3(A→B)

Fig. 13. Session example

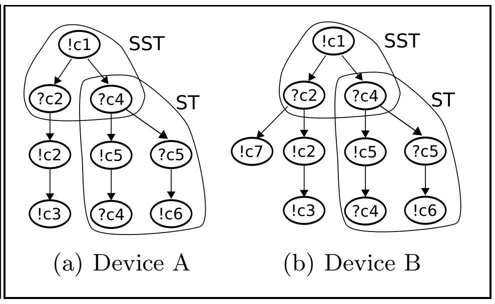


Fig. 14. Kernel trees

6 Behavioral Fingerprinting

In order to best describe our approach, we will use the example illustrated in figure 13. The messages exchanged between two parties are captured first. Secondly, each message can be mapped to the corresponding message type. This is done using the clustering mechanism described previously. Once each message is mapped to its cluster, a session of captured messages can be represented as a sequence of clusters. A session is composed of the messages exchanged between two entities without a relative long inactivity period. in fact, TCP based protocol sessions are easily distinguishable

The original sequence of messages can be mapped to the sequence of clusters:
$\{m_1(A \rightarrow B), m_2(B \rightarrow A), m_3(A \rightarrow B), m_4(A \rightarrow B)\}$
$\equiv \{c(m_1)(A \rightarrow B), c(m_2)(B \rightarrow A), c(m_3)(A \rightarrow B), c(m_4)(A \rightarrow B)\}$
$\equiv \{c_1(A \rightarrow B), c_2(B \rightarrow A), c_2(A \rightarrow B), c_3(A \rightarrow B)\}$
$\equiv \{!c_1, ?c_2, !c_2, !c_3\}_{A \rightarrow B}$

We use the notation ?x for a message x that is received and the notation !x to model that a message of type x is emitted by a device.

A second capture might consist in the sequence of messages (figure 13):
$\{m_5(A \rightarrow B), m_6(B \rightarrow A), m_7(A \rightarrow B), m_8(B \rightarrow A)\}$
$\equiv \{c(m_5)(A \rightarrow B), c(m_6)(B \rightarrow A), c(m_7)(A \rightarrow B), c(m_8)(B \rightarrow A)\}$
$\equiv \{c_1(A \rightarrow B), c_4(B \rightarrow A), c_5(A \rightarrow B), c_4(B \rightarrow A)\}$
$\equiv \{!c_1, ?c_4, !c_5, ?c_4\}_{A \rightarrow B}$

In the same manner, the final capture consists in the sequence:
$\{!c_1, ?c_4, ?c_5, !c_6\}_{A \rightarrow B}$

Then a tree based representation can summarize them as follows: a simple algorithm adds incrementally a sequence to the tree. This is done by checking the longest prefix of the chain that is also a path sourced (in the root) in the tree. Starting with the last node in this path, the remaining suffix is added as a chain to the tree.

We construct for each device, a device specific trees - see figure 14. Each node in the tree corresponds to a message type. An edge in the tree links two nodes if the corresponding message types have been observed to succeed in the traces Although known to be NP complete (see [36],[37] and [38] for good overviews on this topic), the existing heuristics for doing it are based on building tree representations for the underlying finite state machine. In our approach we don't prune the tree and although the final tree representation is dependent on the order in which we constructed the tree, we argue that the resulting substrees are good discriminative features. We follow a supervised training method, where protocol trees are labeled with the identity of their class. The identity of the class is assumed to be known. For instance, the figure 14(a) shows that based on traces, a node can start by sending an INVITE message ($!c1$) and receiving afterwards 180 ($?c2$) or 407 ($?c4$) typed messages. In SIP, a 180 typed message is used to learn that the call in in progress, while 400 messages are related to authentication requests.

The core idea behind behavioral fingerprinting consists in identifying subtrees in the underlying tree representations that can uniquely differentiate between two observed behaviors. We developed a classification method based on trees kernels in order to take into account the peculiar nature of the input space. Tree kernels for support vector machines have been recently introduced in [39], [40], [41] and do allow to use substructures of the original sets as features. These substructures are natural candidates to evaluate the similitude and differentiate among tree-like structures. We have considered two kernel types introduced in [42],[43] and [41]: the subtree (ST) kernel and the subset tree kernel (SST). Simply stated a subtree (ST) of a node is just the complete subtree rooted in that node. A subset tree corresponds to a cut in the tree - a subtree rooted in that node that does not include the original leaves of the tree. For instance, the figure 14 highlights some examples of similar SST and ST for two trees. Figure 14(a) represents a very simple tree corresponding to a Linksys SIP Phone. In the context of behavioral fingerprinting, a device specific protocol tree can be mapped to a set of ST and SST features by extracting all underlying SSTs and STs. Two protocol trees generated by two different devices (figure 14) can now be compared by decomposing each tree in its SSTs and STs followed by a pair-wise comparison of the resulted SSTs and STs. This can be done using tree kernels as proposed in [41]. The idea behind tree kernels is to count the number of similar SSTs in both features sets and/or check the exact matching of underlying STs. The interested reader is referred to [41] for more completeness and fast implementation techniques.

For our purposes, similar substructures correspond to similar behavior in terms of exchanged messages and represent thus a good measure of how much two devices are similar with respect to their behavior. We collected traces from a real VoIP testbed using more than 40 different SIP phones and SIP proxies. In the learning phase, we trained the support vector machines using a modified version of the svm-light -TK [44] developed by Alessandro Moschitti. Our dataset consisted in complete SIP traces obtained during a one day capture from a major VoIP provider. The capture file (8 GB) contained only the signaling SIP related data. Using the user-agent banner, we could identify 40 different end devices. We have also observed traffic coming from user-agents that were not identifiable. This latter is due probably to some topology hiding performed by home routers or session border controllers. For each device/user-agent we constructed the underlying tree representations using a maximum of 300 SIP dialogs. Therefore, devices that generated more than 300 dialogs, were tagged with more than one tree representation. We performed a multi-class classification using the one versus all method described in [41]. The classification precision was 80 % which is a relative promising result. This result was obtained using a 5 fold validation technique - one fifth of the data was taken out and used to assess the accuracy/precision of the system. The remaining four fifths of data was used to train the system. Table 1 summarizes a subset of the SIP devices used for training/testing. We could not include the complete table in the paper due to space constraints. However, the different columns of table 1 give a glance of the data samples and associated tree structures. For instance, the Tribox CE (a popular VoIP PBX) has a tree representation of depth 99 and 279 nodes. This was learned using 1935 messages split over 544 SIP dialogs.

Device	**#Msgs**	**#Sessions**	**#Dialogs**	**#Nodes**	**Depth**
TrixboxCE_v2.6.0.7	1935	714	544	279	99
Twinkle_v1.1	421	129	109	146	36
Thomson2030_v1.59	345	102	83	105	34
Cisco-7940_v8.9	457	175	139	54	18
Linksys_v5.1.8	397	130	67	206	99
SJPhone_v1.65	627	246	210	66	19

Table 1. Tested equipment

7 Conclusion and future work

We have addressed in this paper the automated fingerprinting of unknown protocols. Our approach is based on the unsupervised learning of the types of messages that are used by actual implementations of that protocol. The unsupervised learning method relies on support vector clustering - SVC. Our technique is using a new metric - the weighted character position metric. This metric is computed rapidly and does not suppose any knowledge about the protocols: header fields specification, number of messages. One main advantage of the SVC technique is its improvement of the accuracy of the classification for large datasets. We have also proposed a semi automated method that allows to choose the best parameters. The observed message types can be used to induce a tree-like representation of the underlying state machines. The nodes in this tree represent the different types of observed messages and the edges do indicate an invocation relationship between the nodes. This first phase is completed by a second stage, where the behavioral differences are extracted and mined. This second phase uses tree kernel support vector machines to model the finite state machines induced from the first phase. The main novelty of this approach lies in the direct usage and mining of the induced state machines. We did test our approach on extensive datasets for several well known protocols: SIP, SMTP and IMAP. The observed empirical accuracy is very good and promising. We plan to extend this work towards other machine learning tasks and conceptual solutions. In addition, finding specific metrics for encrypted and binary protocols is another direction for future work.

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