Automated IoT Device Fingerprinting Through Encrypted Stream Classification

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Abstract. The explosive growth of the Internet of Things (IoT) has enabled a wide range of new applications and services. Meanwhile, the massive scale and enormous heterogeneity (e.g., in device vendors and types) of IoT raise challenges in efficient network/device management, application QoS-aware provisioning, and security and privacy. Automated and accurate IoT device fingerprinting is a prerequisite step for realizing secure, reliable, and high-quality IoT applications. In this paper, we propose a novel data-driven approach for passive fingerprinting of IoT device types through automatic classification of encrypted IoT network flows. Based on an in-depth empirical study on the traffic of real-world IoT devices, we identify a variety of valuable data features for accurately characterizing IoT device communications. By leveraging these features, we develop a deep learning based classification model for IoT device fingerprinting. Experimental results using a real-world IoT dataset demonstrate that our method can achieve 99% accuracy in IoT device-type identification.

Keywords: IoT · Device fingerprinting · Encrypted traffic analysis.

1 Introduction

Recent years have witnessed the explosive growth of the Internet of Things (IoT), where smart objects such as cameras, printers, and routers are interconnected to facilitate a wide range of new applications and services (e.g., smart home and smart city). According to a Gartner report [2], over 20 billion devices will be connected to Internet by 2020. Meanwhile, the enormous heterogeneity and vast scale of IoT raise challenges in efficient network/device management, application QoS provisioning, and security and privacy. The proliferation of security vulnerabilities has promoted the emergence of a new generation of malware [9, 20, 13] that target explicitly at IoT devices. For example, the Mirai [9] malware compromised over one million IoT devices and conducted DDoS attacks against several major server infrastructures.

Automated and accurate identification of IoT device types (i.e., device fingerprinting) is a crucial prerequisite for realizing secure, reliable, and high-quality IoT applications. From the perspective of device management, each IoT device has to be individually configured depending on its type. Given the sheer number of heterogeneous devices deployed in a smart environment, manual configuration is onerous and error-prone. To achieve application QoS guarantee, different priorities may be assigned to devices of different types. In Internet of Vehicles (IoV), it is imperative to prioritize network flows conveying traffic emergency information over those from entertainment devices under high traffic load. To ensure network security, vulnerable devices should be provisioned with more restricted security rules.

In recent years a variety of techniques for IoT device fingerprinting have been proposed [9, 6, 14, 15, 24, 26, 27]. One major approach employs active banner grabbing [9, 6, 14, 15] to collect device-specific information from the application-layer responses and identifies device types based on a database of matching rules. Unfortunately, this approach is inapplicable to fingerprinting IoT devices that adopt SSL/TLS to secure their communications.

Another avenue of research tackled device fingerprinting through passive IoT traffic classification [24, 26, 27]. However, none of these approaches is manifested to be effective in accurately classifying encrypted IoT traffic. Moreover, most of them merely leverage limited set of traffic features, thus suffering from classification performance degradation in case that sophisticated malware is capable of altering a device's communication pattern.

In this paper, we propose a passive data-driven approach for automated IoT device fingerprinting through encrypted flow classification at the network edge. Motivated by the limitations of prior works, we identify two challenges associated with encrypted flow classification based IoT device fingerprinting. First, IoT devices increasingly use SSL/TLS to secure their communications. Therefore, it is infeasible to collect application-layer data about IoT devices through deep packet inspection (DPI), which necessitates accurate yet privacy-preserving method for classifying IoT traffic. Second, since the IoT traffic only accounts for a minor portion of the entire Internet traffic, identifying IoT traffic from the remaining network traffic is largely a needle-in-the-haystack problem. This situation is worsened by the heterogeneous deployment of traditional and IoT devices in real-world IoT environment.

To resolve these challenges, we first propose to collect substantial telemetry information about IoT device communications at the network edge. Based on these information, we identify and extract a wide range of data features to characterize the network flows generated by both IoT and conventional non-IoT devices. Our feature set comprehensively integrates traditional flow features, device-specific behavioral features, and TLS-related features by analyzing the unencrypted TLS handshake data. The collection of these features does not require packet payload analysis through DPI, making it applicable to the characterization of encrypted IoT traffic. To demonstrate the potential of the identified features for IoT device fingerprinting, we perform an in-depth empirical analy-

sis over real-world IoT traffic with a focus on characterizing the disparate TLS usage of IoT devices.

Second, leveraging these data features collectively, we use supervised machine learning (ML) classifiers to accurately differentiate between IoT traffic and non-IoT traffic relevant to typical client-server applications. For the purpose of IoT device fingerprinting, we develop a deep learning based multinomial classifier to classify encrypted IoT TLS flows. Our classification model can achieve 99% accuracy for IoT device fingerprinting based on the classification of single network flow, which is more responsive than prior multi-flow based classification methods. Moreover, using all available data features considerably enhances the robustness of the fingerprinting method. Compared to fingerprinting techniques that leverage limited features (e.g., packet sizes and timing), our approach is more resilient against sophisticated attackers that can obfuscate IoT device traffic.

In summary, we make the following contributions:

- We perform an in-depth empirical analysis of SSL/TLS encrypted IoT traffic and identify a variety of valuable data features for accurately characterizing IoT device communications.
- We propose a novel data-driven approach for passive fingerprinting of IoT device types based on automated classification of encrypted TLS flows of IoT devices.
- We develop a deep learning based classification model for IoT device fingerprinting. Using a large dataset consisting of 21 real-world IoT devices, our model can achieve 99% accuracy in IoT device-type identification.

The remainder of the paper is organized as follows. Section 2 introduces the assumptions and the used dataset. Section 3 gives an overview of the proposed approach. Section 4 discusses the feature extraction process in detail. An empirical analysis of IoT TLS usage is presented in Section 5. Section 6 presents the evaluation results. Discussion and related work are presented in Section 7 and 8, respectively. Section 9 concludes the paper.

2 Assumptions and Data Preliminaries

The IoT fingerprinting scenario we consider is a typical local area network (e.g., enterprise network or campus network), as shown in Figure 1, where a large range of IoT devices and non-IoT devices are deployed heterogeneously. The devices connect to the Internet via an access gateway. Common encryption techniques such as SSL/TLS can be employed by the devices to ensure data privacy and integrity.

The primary goal of IoT device fingerprinting is to identify the semantic type of new or unseen devices connected to the local network by solely relying on network traffic classification. For this purpose, our traffic analysis assumes a role of passive observer with the capability of monitoring the traffic traversing the gateway router. The raw packets can be collected using common packet capturing

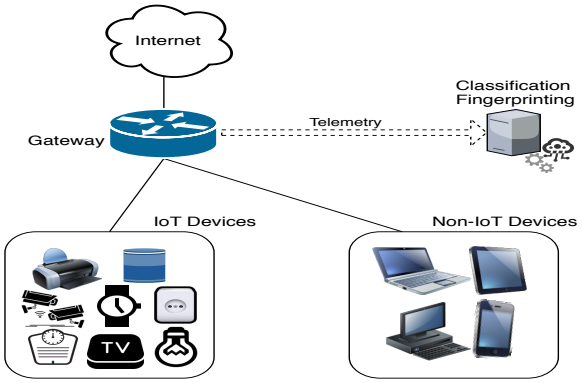


Fig. 1. Edge-based IoT Device Fingerprinting

libraries, such as tshark [25] and NFQueue [33]. We do not manipulate the network traffic (e.g., deep packet inspection) or use the packet contents. Instead we extract useful telemetry information from the raw packets (e.g., protocol headers and traffic statistics) and leverage the information for IoT device fingerprinting.

Data preliminaries. The dataset used in our analysis was originally collected by Sivanathan et al. [32] in a smart environment as depicted in Figure 1. It contains traffic from 21 IoT devices (e.g., smart cameras and switches) and 3 non-IoT devices over 3 weeks operation. We observe that 14 out of 21 IoT devices use TLS to secure their communications, which accounts for 55% of the total captured IoT traffic.

3 Approach Overview

In this section we define the problem of IoT device fingerprinting and present an overview of our fingerprinting approach.

3.1 Problem Definition

We formulate IoT device fingerprinting as a classification problem. That is, we perform supervised multi-class classification, where a classifier is trained on labeled instances and tested by assigning a label out of multiple predefined labels to each unlabeled instance. Given a set of IoT device types $D = \{d_1, \ldots, d_n\}$, each instance is of the form $(\mathbf{f_i}, d_i)$, where $\mathbf{f_i}$ is the feature vector that represents a network flow (i.e., a bidirectional flow defined by the network five-tuple) generated by a device d_i that belongs to D. This way, IoT device fingerprinting is stated as follows: assign a device type in D to each new network flow based on its features.

3.2 Overview

The IoT device fingerprinting framework is composed of four major components: *packet capture/parsing*, *feature extraction*, *classifier training*, and *device type fingerprinting*.

Packet capture/parsing. Traffic from devices in the monitored network are collected with common packet capturing libraries such as tshark and NFQueue. The raw packets are parsed and reassembled into successive bidirectional flows based on the *flow key* represented by conventional network five-tuple: the source and destination addresses, the source and destination ports (for TCP and UDP traffic), and the protocol number.

Feature extraction. We identify and extract a series of network flow features from the reassembled flows, which uniquely characterize the IoT device traffic. These features not only allow to distinguish IoT traffic from conventional network traffic, but also enable accurate IoT device fingerprinting. We classify these features into two broad categories: aggregate and intraflow features. Aggregate features characterize flow statistics and device activities spanning multiple flows. Intraflow features consist of flow metadata (from packet header), time-series features (e.g., packet lengths and inter-arrival times), and TLS-related features (for SSL/TLS encrypted traffic). All the extracted m features are represented as a vector $\mathbf{f} \in \mathbb{R}^m$. The feature extraction process is elaborated in Section 4.

Classifier training. This component is responsible for creating ML-based classifiers through model training based on the extracted flow features. We could build binary classifier to differentiate IoT devices from conventional non-IoT devices. For the task of IoT device fingerprinting, a multiclass classifier is trained on the labeled instances ($\mathbf{f_i}$, d_i). The resulting model is stored for IoT device type fingerprinting.

Device type fingerprinting. For a new flow represented by the feature vector $\mathbf{f}$, the trained classifier C is applied to identify the device type. Classifier C outputs a vector of posterior probabilities $\mathbf{p} = \{p_1, \ldots, p_n\}$, where p_i is the probability of flow $\mathbf{f}$ originating from device d_i. The device type is identified as the d_i with maximal probability.

4 Feature Extraction

Feature extraction is the process of transforming real world observation into a vector of values that describe the underlying process. With the purpose of IoT device fingerprinting, we identify a series of network flow based features that uniquely characterize the IoT traffic. These features not only allow us to distinguish IoT traffic from conventional network traffic, but also enable accurate IoT device fingerprinting. We classify these features into two broad categories: aggregate (interflow) and intraflow features. Intraflow features consist of the normal flow features, "side-channel" features, and TLS-related features (for SSL/TLS encrypted traffic). In contrast, aggregate features are interflow features that characterize flow statistics and device activities spanning multiple flows.

Here we elaborate on the feature extraction process and explain the rationale of leveraging these features for encrypted flow classification.

4.1 Aggregate Features

IoT traffic typically constitutes (1) background traffic generated by the device autonomously (e.g., NTP queries for time synchronization) and (2) traffic generated due to user interactions (e.g., the smart camera transmits image data to the cloud server when home invasion occurs). Aggregate features provide a high-level characterization of device activities. They are collected from multiple consecutive flows within specific duration. One such feature is the interflow time during which the IoT devices remain inactive, as it indicates the overall frequency of device activity. For this we compute the mean and standard deviation of the interflow times as features.

We also identify other device-specific aggregate features including the respective numbers of involved application-layer protocols, contacted destination servers, and unique DNS queries issued by the device within a fixed duration. We analyze the IoT dataset discussed in Section 2 and compute the daily average of the three aggregate features for each device. As indicated in Figure 2, each IoT device presents a distinct profile of feature combination. Compared to non-IoT devices (as listed in Table 1), IoT devices communicate with significantly fewer destination servers and generate fewer unique DNS queries accordingly. The application protocols involved in IoT communication are more restricted. This is intuitively reasonable since the majority of IoT devices are purpose-limited with restricted functionality (e.g., transmitting data to the cloud server for processing or receiving commands from the control server), while the real user/application behavior is enormously heterogeneous.

Table 1. Aggregate Features of Non-IoT Devices

Non-IoT Device	Destination Servers	Application Protocols	Unique DNS Requests
MacBook Pro	985	6	193
Android Smartphone	348	7	184
Windows PC	862	8	205

4.2 Intraflow Features

Flow Metadata. Flow metadata includes useful information conveyed by the packet header and statistical features of the entire flow. The features we extract include the source and destination ports, the number of inbound/outbound packets and bytes, the total duration of the flow in seconds, the mean packet size, and the peak and mean packet rate. Due to the dynamic allocation of IP addresses and the widespread use of CDNs, we exclude IP addresses from the feature set.

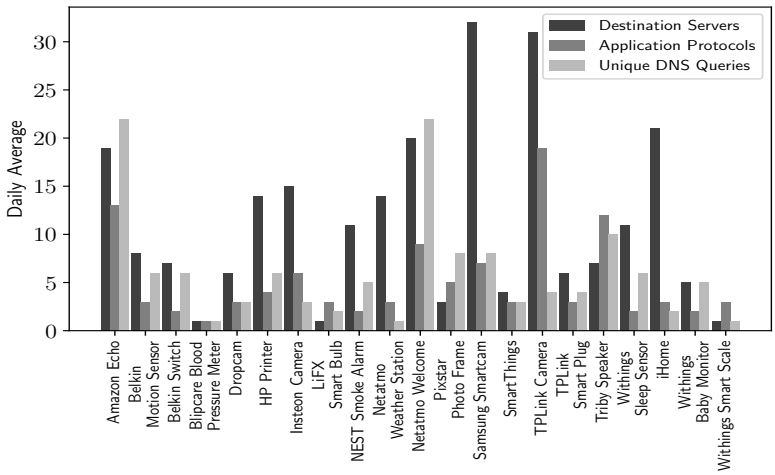


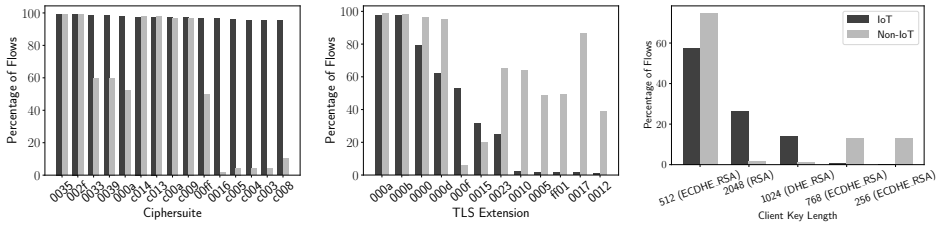
Fig. 2. Aggregate Features of IoT Devices

Since IoT devices typically generate short bursts of traffic sporadically [32], these per-flow features serve as coarse-grained description of IoT device activity.

Packet Sizes and Inter-arrival Times. The series of packet sizes and inter-arrival times within a flow reveal the fine-grained pattern of IoT communication. From the application level, these features provide a descriptive profile of user behavior. For example, an IoT device such as a smart camera may periodically transmit packets of uniform size to its cloud server; while a PC would generate flows with more diversity in the packet sizes/inter-arrival times given the complexity of user activities (e.g., web browsing and video streaming).

For each flow the packet sizes and inter-arrival times are extracted without considering the TCP retransmission packets or packets lacking payloads (e.g., pure TCP ACK). We used Markov chain to model the time series features. To model the series of packet sizes, we separate the IP MTU size into equally sized bins $B = \{b_1, \ldots, b_n\}$ and allocate each packet size value to the appropriate bin. A matrix S is constructed where each entry, $S[i, j]$, keeps track of the number of transitions between the bin b_i and bin b_j. We then normalize each entry of S as the transition probability and flattened S into a feature vector. The series of packet inter-arrival times is modeled in the same way.

Byte Distribution. The full byte distribution provides information about the encoding of the data. This feature is modeled as a histogram giving the frequency of occurrence for each byte value in the application payload for a flow. Specifically, we used an array to record the count for each byte value of the packet payloads in a single flow. In our analysis an array length 256 is adopted. The probability of each byte value is computed by dividing the byte counts by the total number of byte counts recorded by the array.



a. Advertised Ciphersuites b. Advertised Extensions c. Public Key Length

Fig. 3. TLS Client Features for IoT versus Non-IoT Devices.

Unencrypted TLS Handshake Information. Even for SSL/TLS encrypted traffic, we can still extract valuable information from the unencrypted TLS handshake process. Such information serves as characteristic feature of the communication endpoints. The `ClientHello`, `ServerHello` and `Certificate` messages contain plain text data. In particular, the `ClientHello` message advertises lists of supported ciphersuites and TLS extensions ordered by the client preference. The `ServerHello` message conveys the ciphersuite and TLS extensions selected by the server. The server certificate information can be derived from the `Certificate` message. The client public key length can be determined from the length of the `ClientKeyExchange` message.

Our classification model uses the list of offered ciphersuites, the list of advertised extensions, and the public key length as features. In total 124 unique ciphersuites were observed in the dataset, and a binary vector of length 124 was created where a one is assigned to each ciphersuite in the list of offered ciphersuites. We also observed 14 unique TLS extensions, and a binary vector of length 14 was created where a one is assigned to each extension in the list of advertised extensions. The public key length was represented as a single integer value. Therefore, we extracted 139 TLS features for classification.

To demonstrate the discriminatory power of TLS features for IoT device fingerprinting, in Section 5 we provide a detailed characterization of TLS usage in IoT.

4.3 Integration of Aggregate and Intraflow features

To integrate aggregate features with the intraflow features, we used a disjoint sliding window method to calculate the aggregate features within the window, and then augment each intraflow feature vector within a window with the corresponding aggregate features.

5 Characterizing TLS Usage in IoT

In this section, we compare the TLS usage of IoT devices with conventional non-IoT devices and show that they exhibit distinct characteristics. From the

dataset we extract 7820 unique TLS flows of 9 IoT devices and 12557 flows of 3 non-IoT devices. Each unique flow originates from a successful TLS handshake. Merely 12 or less unique flows are extracted from 5 IoT devices, which may be attributed to the extensive use of TLS session resumption to avoid expensive TLS renegotiation. In fact we observed that 25% of IoT clients advertised the `0x0023 (SessionTicket TLS)` extension.

5.1 TLS Client Features

The difference between IoT and non-IoT devices regarding the TLS client features is manifested in Figure 3. First, the top 15 most advertised ciphersuites in IoT are listed along with the corresponding percentage in non-IoT flows. We see less variation in the distribution of the offered ciphersuites in IoT as IoT devices consistently advertise limited and fixed number of ciphersuites. In contrast, due to the diversity in applications, larger variation in ciphersuite distribution is observed in non-IoT traffic. Nearly 100% of IoT devices offer weak ciphersuites such as `0x000a(TLS_RSA_ WITH_3DES_EDE_CBC_SHA)`, `0x0016(TLS_DHE_RSA_WITH_3DES_EDE_CBC_SHA)`, `0xc003 (TLS_ECDH_ECDSA_WITH_3DES_EDE_CBC_SHA)`; while non-IoT devices advertise them with significantly lower frequency. This implies that TLS implementations in IoT may be outdated or lack thorough security considerations.

Table 2. TLS client features for each IoT device.

Device Category	Number of Unique TLS Feature Vectors	Number of Offered Ciphersuites	Number of Offered Extensions	Most Frequently Advertised Extensions	Client's Public Key
Amazon Echo	2	91	7	heartbeet supported_groups ec_point_formats	2048-bit (RSA) 512-bit (ECDHE_RSA)
Dropcam	1	3	4	SessionTicket TLS heartbeat supported_groups ec_point_formats	512-bit (ECDHE_RSA)
HP Printer	4	85	13	signature_algorithms	768-bit (DHE_RSA) 2048-bit(RSA)
Netatmo Welcome	2	69	5	server_name supported_groups ec_point_formats	512-bit (ECDHE_RSA)
PIX-STAR Photo-frame	1	79	6	All 6 extensions	1024-bit (DHE_RSA)
Samsung Smartcam	1	49	4	All 4 extensions	512-bit (ECDHE_RSA)
SmartThings	1	1	1	signature_algorithms	1024-bit (DHE_RSA)
Triby Speaker	1	80	8	All 8 extensions	512-bit (ECDHE_RSA)
iHome	1	8	1	signature_algorithms	2048-bit (RSA)
Android Smartphone	14	78	14	supported_groups ec_point_formats signature_algorithms	512-bit (ECDHE_RSA) 768-bit (DHE_RSA) 256-bit (ECDHE_RSA) 2048-bit (RSA) 1024-bit (DHE_RSA)
MacBook Pro	9	89	14	supported_groups ec_point_formats	512-bit (ECDHE_RSA) 768-bit (DHE_RSA) 256-bit (ECDHE_RSA) 2048-bit (RSA) 1024-bit(DHE_RSA)
Windows PC	7	96	14	supported_groups ec_point_formats	512-bit (ECDHE_RSA) 768-bit (DHE_RSA) 256-bit (ECDHE_RSA) 2048-bit (RSA) 1024-bit(DHE_RSA)

We also observed more diverse distribution in TLS extensions advertised by non-IoT devices. Up to 8 extensions are advertised in over 50% of non-IoT flows. In contrast, only 4 extensions are advertised by 50% of IoT flows. Three extensions were advertised in over 50% of non-IoT flows and rarely observed in IoT flows: `0x0017 (extended_master_secret)`, `0x0010 (ALPN)`, and `0xff01 (renegotiation_info)`. This indicates more lightweight TLS implementation with limited functionality in IoT due to the computation and resource constraint. We also observed that the extension `0x000f (heartbeat)` is advertised with a much higher frequency by IoT devices which indicates the behavior of IoT devices frequently contacting remote servers for liveliness check. Moreover, 40% of IoT clients advertised `0x0015 (padding)` extension compared to 20% of the enterprise clients, which indicates the existence of more aged IoT clients that have outdated TLS implementation.

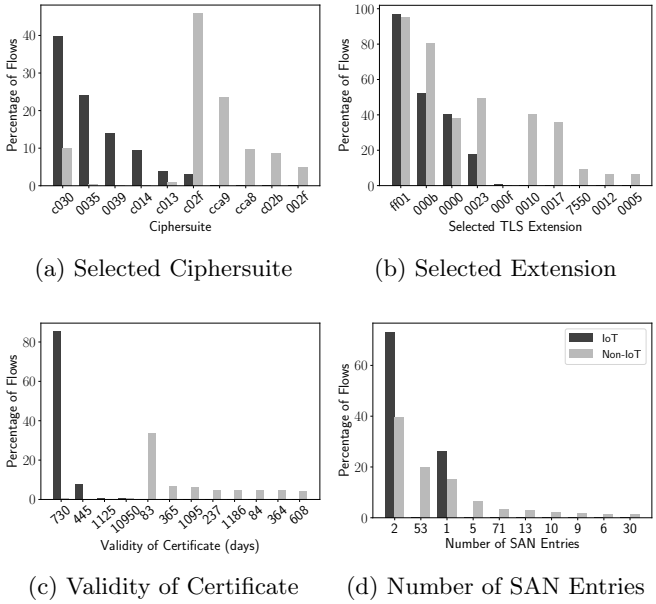
The distribution of client public key length is also different. Most non-IoT devices used a 512-bit (ECDHE_RSA) public key. 2048-bit (`RSA`) and 1024-bit (`DHE_RSA`) were more widely used by IoT devices. One interesting observation is 27% of non-IoT flows used 256-bit (`ECDHE_RSA`) to generate keys for `CHACHA20_POLY130` cipher, but no IoT clients used this cipher to encrypt their connection.

The discriminatory power of TLS client features for IoT device fingerprinting becomes more obvious when looking into the TLS usage of each device. Table 2 summarizes the TLS client features for each device. Four IoT devices offered the number of ciphersuites comparable to the non-IoT devices, while only one IoT device (i.e., HP Printer) offered the same number of extensions. The public keys used by the IoT devices are also quite limited with all devices using at most two public keys for their connections, which indicates the simplicity of IoT devices. In contrast, we observed more variation in the used public keys in non-IoT devices due to the diversity of user applications.

Table 2 also lists the number of unique TLS client feature vectors advertised by each device. Here a feature vector is considered unique if the concatenation of ciphersuite and extension features is different. We can see that each IoT device offered quite distinct ciphersuites and extensions, which allows accurate identification of the specific device category. 6 out of 9 IoT devices even consistently offered a single fixed set of ciphersuites and extensions. 2 IoT devices offered 2 ciphersuite vectors and only the HP Printer offered 4. This also implies that IoT devices typically employ the same client to communicate with the remote servers.

5.2 TLS Server Features

Figure 4 illustrates the difference regarding TLS server features. 60% of TLS sessions selected `0xc030 (TLS_ECDHE_RSA_WITH_AES_256_GCM_SHA384)` and 25% of TLS sessions selected `0x0035 (TLS_RSA_WITH_AES_256_CBC_SHA)`. In contrast, the distribution of ciphersuites selected by non-IoT device sessions is more heavily tailed. This corroborates the client-side analysis that most IoT devices used specialized clients to communicate with limited number of remote servers.



(a) Selected Ciphersuite (b) Selected Extension

(c) Validity of Certificate (d) Number of SAN Entries

Fig. 4. TLS Server Features for IoT versus Non-IoT Devices.

Similar to the selected ciphersuites, the servers that IoT devices communicated with selected fewer TLS extensions. There is much greater diversity in the selected TLS extensions with `0xff01 (renegotiation_info)` and `0x000b (ec_point_formats)` being the most frequent.

By analyzing the plain text server certificate data (e.g., certificate subject), we found that non-IoT devices mostly connected to common servers such as `*.google.com`, `*.icloud.com` and `*.facebook.com`. Moreover, the corresponding distribution of certificate subjects is very long tailed. We also analyzed two other features extracted from server certificates: the certificate validity and the number of `Subject Alternative Name (SAN)` entries. As depicted in Figure 4, the validity of the certificate is sharply divided for IoT devices and non-IoT devices. The distribution of the validity of non-IoT devices' certificates is long tailed with greater diversity. Almost all server certificates associated with IoT devices have no more than 2 SAN entries. This is intuitively reasonable considering that non-IoT devices typically connected with several hundreds of distinct servers in a single day, whereas IoT devices only consistently communicate with its manufacture server or third-party cloud server for data uploading and processing.

Table 3 summarizes the TLS server features for each device. A unique combination of ciphersuite and extension is selected in IoT TLS flows. Due to the abundance of client applications, TLS sessions of non-IoT devices selected more diverse ciphersuites and extensions. Especially when considering the respective

Table 3. TLS server features for each device.

Device Category	Most Frequently Selected Ciphersuite	Most Frequently Selected Extensions	Number of Distinct CS	Number of SAN entries	Number of Distinct SNI
Amazon Echo	TLS_ECDHE_RSA_WITH_AES_128_GCM_SHA256	renegotiation_info server_name ec_point_formats	1	2	5
Dropcam	TLS_ECDHE_RSA_WITH_AES_128_CBC_SHA	renegotiation_info	1	2	0
HP Printer	TLS_DHE_RSA_WITH_AES_128_CBC_SHA	renegotiation_info	2	3	0
Netatmo Welcome	TLS_ECDHE_RSA_WITH_AES_256_GCM_SHA384	renegotiation_info server_name ec_point_formats	1	2	1
PIX-STAR Photo-frame	TLS_DHE_RSA_WITH_AES_256_CBC_SHA	renegotiation_info SessionTicket TLS	1	1	1
Samsung SmartCam	TLS_DHE_RSA_WITH_AES_128_CBC_SHA	renegotiation_info ec_point_formats SessionTicket TLS	1	1	0
SmartThings	TLS_DHE_RSA_WITH_AES_128_CBC_SHA	signature_algorithms	2	0	0
Triby Speaker	TLS_ECDHE_RSA_WITH_AES_256_GCM_SHA384	renegotiation_info heartbeat server_name ec_point_formats	1	0	1
iHome	TLS_RSA_WITH_AES_128_CBC_SHA256	None	1	2	0
Android Smartphone	TLS_RSA_WITH_AES_128_CBC_SHA	renegotiation_info	135	53	263
MacBook Pro	TLS_ECDHE_RSA_WITH_AES_128_GCM_SHA256	renegotiation_info	148	53	316
Windows PC	TLS_RSA_WITH_AES_256_CBC_SHA	renegotiation_info	262	53	554

numbers of certificate subjects, SAN entries and unique server name indication (SNI) fields, we can observe significant difference between both categories of devices.

5.3 Discriminative Power of TLS Features

Figure 5 shows a similarity matrix for the 14 IoT devices with respect to their TLS clients. The client offered ciphersuites, the advertised extensions and the public key length were concatenated as feature vectors, and the similarity between two feature vectors was computed using Euclidean distance (2-norm) $d(f_i, f_j) = \sqrt{\sum_{i,j}(f_i - f_j)^2}$ as the distance metric, and f_i being the mean of the feature vectors for the i'th device type. Since each IoT device should be perfectly self-similar, the diagonal of this matrix are all 1.0. The TLS client feature for each IoT device is unique except for the Belkin Motion Sensor and the TPLink Smart Plug, which have similar TLS client parameters. Device-specific TLS parameters can be a promisingly powerful feature for classifying IoT device type.

6 Evaluation

In this section, we describe the details of our ML-based IoT fingerprinting methodology, and demonstrate the discriminative power of the TCP/IP flow features for accurately differentiating between IoT devices and non-IoT devices as well as identifying the specific IoT device category.

6.1 Algorithms

We performed the encrypted flow classification using a deep learning based model: Multi-layer Perceptron (MLP), and compared the results with three com-

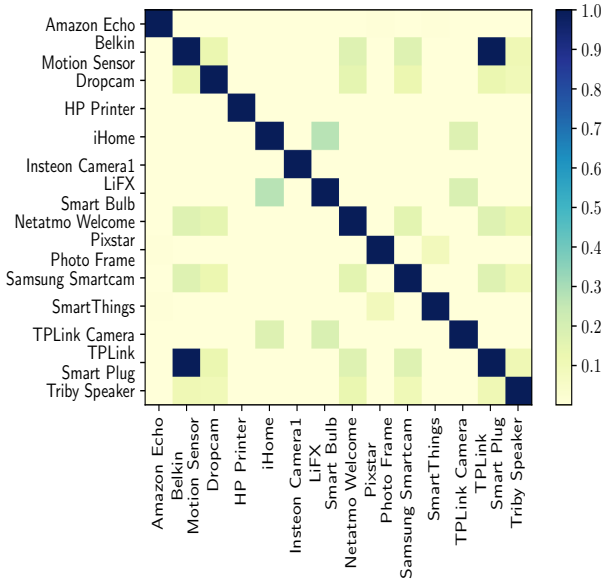


Fig. 5. Similarity matrix for different IoT devices with respect to the TLS client features

mon machine learning algorithms: Logistic Regression, Random Forest and Support Vector Machine. To auto-tune the hyperparameters for the models, we used grid search and cross-validation over a set of standard values. We used Keras [5] with the TensorFlow [7] backend to implement the MLP; while the remaining ML algorithms are implemented using Scikit-learn [28]. An open source tool is used and extended for feature extraction [4].

Multi-layer Perceptron (MLP). MLPs are fully connected feed-forward neural networks with multiple hidden layers. Each layer consists of several neurons that compute a weighted sum of the inputs from the adjacent layer and produce the output through a non-linear activation function. Deep and dense MLPs can estimate highly nonlinear functions. However, due to the huge number of parameters that need to be learned, it is complex process to train these models and there is the potential for overfitting.

We performed automatic search of the best hyperparameters for the MLP model using grid search and cross validation. Table 4 lists the values of the hyperparameters we tuned and the corresponding intervals within which the values are varied.

Logistic Regression. Logistic regression is one of the simplest classification algorithms. It generates an estimate of the probability that a feature vector belongs to a specific class. We used both l1-regularization and l2-regularization in the comparison. The model is more easily interpretable compared to MLP

Table 4. Tuned hyperparameters of the MLP

Hyperparameter	Value	Tuning Space
optimizer	Adam	Adam, SGD, RMSProp
learning rate	0.001	0.001 .. 0.1
momentum	0.0	0.0 .. 0.9
batch size	32	8 .. 256
training epochs	150	50 .. 200
number of hidden layers	3	2 .. 5
dropout	0.1	0.0 .. 0.5
activation	sigmoid	tanh, sigmoid, relu

as the model parameters quantify the significance of the corresponding data features.

Random Forest. A random forest combines decision tress with ensemble learning [10]. Each decision tree is built from a random sub-sample of the original data and produces a probability for each possible output class. The output of the ensemble is the average probability among all decision trees. Random forest is resistant to overfitting. Moreover, the variance is reduced without resulting in bias when the number of trees increases. For the Scikit-learn implementation, we used grid search and cross-validation to tune the depth of the trees and the number of features per split.

Support Vector Machine (SVM). An SVM projects original data to a high-dimensional feature space using a kernel function, where a hyperplane can be built to linearly separate different classes [12]. Our SVM implementation adopts the One-VS-Rest strategy and uses LinearSVC for classification.

6.2 IoT vs Non-IoT

For the binary classification between IoT and Non-IoT device flows, we used a logistic regression classifier with l1-regularization [18]. As such, five machine learning classifiers were trained using different combinations of the collected data features, which incorporate the flow metadata (M), the time series features including the packet sizes (PS) and inter-arrival times (PT), the byte distribution of the packet payload (BD), the TLS client parameters (i.e., the offered ciphersuites, advertised extensions, and the public key length) (TLS), and the aggregate features (A) spanning multiple flows.

To demonstrate the usefulness of the identified data features, we use 10-fold cross validation over 96680 IoT flows and 96680 Non-IoT flows, out of which 20000 flows are TLS flows. Table 5 shows the cross validation results. We can see that using all available data features achieves the best accuracy of 99.6%. Using the TLS features alone to classify TLS flows gives 90% accuracy, which demonstrates the usefulness of these features for characterizing IoT devices.

Table 5. Classifier accuracy for different subsets of features

Data Features	Accuracy
M+PS+PT	82.4%
M+PS+PT+BD	93.5%
TLS	90.1%
M+PS+PT+BD+TLS	97.2%
M+PS+PT+BD+TLS+A	99.6%

6.3 IoT Device Fingerprinting

We also evaluate the effectiveness of the identified flow features for IoT device fingerprinting. For the multi-class classification, we use 541250 flows generated by all the 21 IoT device categories and data features described in Section 4. We randomly selected 75% flows to train the classifiers and used the remaining 25% flows for testing. The final classification results under different ML models are listed in Table 6. Using MLP and all flow features results in the best classification performance, with an overall accuracy of 99.8% for the 21-class classification based on a single network flow.

Table 6. Comparison of classifier performance

Model	Accuracy
$l1$-Logistic Regression	86.2%
$l2$-Logistic Regression	81.5%
Random Forest	72.7%
SVM	58.4%
MLP	**99.8%**

The confusion matrix of the best classification result is shown in Figure 6. Each matrix element m_{ij} represents the percentage of device d_i's flows classified as that of device d_j. The confusion matrix is perfectly diagonal, indicating the superior power of the identified network flow features for IoT fingerprinting. Notably, all samples of an Insteon Camera were identified as another device of the same category since it generated significantly less flows.

We also present the classification performance of MLP with different subsets of features in Table 7. With a subset of data features, our approach is able to differentiate the device types based on a single flow. Using a combination of the available data features significantly enhances the classification robustness.

6.4 Algorithm Performance

We assess the performance of the used classification algorithms in terms of the training and testing time. The multi-class classification experiment discussed in Section 6.3 was repeated 10 times for each algorithm. Figure 7 and Figure 8 plot

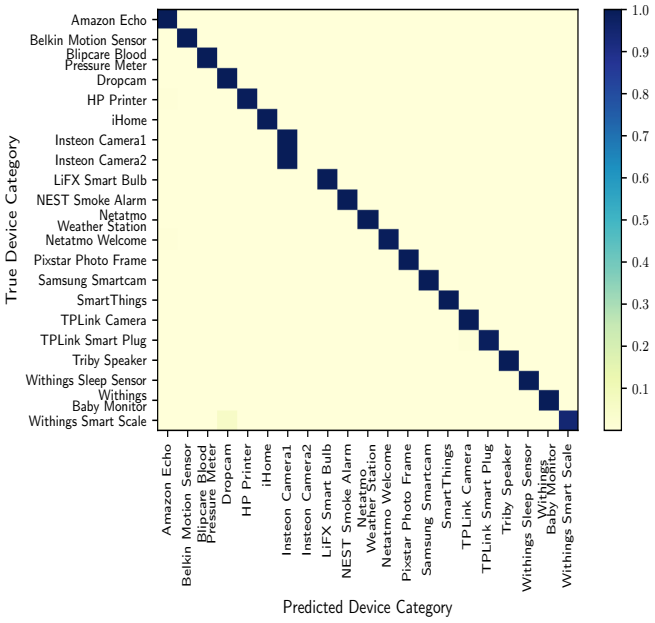


Fig. 6. Confusion matrix for the 21-class IoT device type classification using MLP. The best overall accuracy is 99.8%.

Table 7. MLP classification accuracy for different subsets of the flow features

Data Features	Accuracy	Precision	Recall
M+PS+PT	0.81	0.84	0.82
M+PS+PT+BD	0.83	0.86	0.83
M+PS+PT+TLS	0.89	0.90	0.89
M+PS+PT+BD+TLS	0.92	0.93	0.93
M+PS+PT+BD+TLS+A	0.99	0.99	0.99

the training and testing times in seconds with respect to the average classification accuracy of each algorithm. The random forest can be quickly trained and tested, while SVM is relatively slow to train and test. The MLP is cumbersome to train, but quick to classify new samples.

7 Discussion and Future Work

Robustness against adversarial attacks. Attackers capable of controlling their devices' network traffic may attempt to circumvent our fingerprinting technique. For example, random or constant delays could be introduced into a flow. Similarly, packet sizes could be varied through data padding at different protocol levels. Since our method does not solely rely on a single feature (e.g., time series

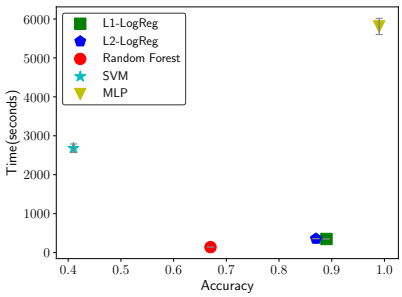


Fig. 7. Model Training Times

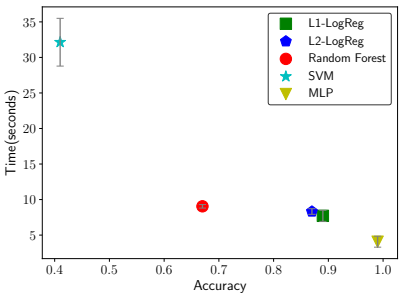


Fig. 8. Model Testing Times

feature), it is more resilient to such adversarial attacks compared to existing IoT device fingerprinting techniques. Modifying the TLS parameters supported by a device (i.e., advertised ciphersuites and extensions) may also degrade the normal functionality of the device itself. An attacker could also try to mimic the traffic pattern of a different device type. Considering that most IoT devices will communicate with a fixed set of servers, it would be extremely difficult for the attacker to generate similar requests to the servers, especially when the emulated device uses TLS for authentication and data encryption.

Impact of TLS 1.3. The analysis of TLS features in this paper is based on TLS 1.2. TLS 1.3 [3] eliminates a complete round trip time, making TLS more suitable for IoT devices. In TLS 1.3, the server selected extensions and certificate get encrypted. Since our approach only relies on TLS client features, the adoption of TLS 1.3 will not deteriorate the performance of IoT device fingerprinting.

Scalability. The proposed IoT device fingerprinting method can be deployed at the edge of a LAN. Our current implementation is applied to small scale IoT smart environment. A more scalable fingerprinting system could be realized using a distributed design. In our future work, we will explore using federated learning approach [21] for distributed optimization of our deep learning based fingerprinting model. Using federated learning, we could train a local model at the network edge and synchronize the model modifications through a centralized server. This solution is more scalable since only model parameters have to be synchronized, thus obviating the need to offload raw data to the centralized server.

Applications of device fingerprinting. In future work, we will consider the applications of automated IoT device fingerprinting from various perspectives. One potential application is to leverage device fingerprinting to instruct the QoS-aware provisioning of network resources. Another focus is on its security applications. For example, we will explore how to integrate our fingerprinting method into existing network access control (NAC) system. This could enable the NAC system to automatically detect unknown vulnerable devices and configure security rules accordingly.

8 Related Work

Operating System Fingerprinting. In network security, fingerprinting has been used for information gathering and vulnerability assessment of the attack target. One prominent example is OS fingerprinting, which aims at determining the operating system of a remote host based on the implementation differences of a TCP/IP network stack. A variety of tools (Nmap [1] and P0f [35]) actively probe a target with purposely crafted packets and generate fingerprint from the response packets. The OS version is identified by matching the fingerprint with a database of existing OS categories. Hershel [30] and Faulds [31] focus on Internet-wide single-probe OS fingerprinting, which leverages the temporal features (i.e., TCP retransmission timeout) to classify the OS of the target. The objective of our work is to identify the IoT device type instead of the OS version, which precludes the usage of OS fingerprinting as different devices may run the same OS.

IoT Device-Type Identification. Various prior research have been proposed to utilize a multitude of data sources for passive IoT device type identification. Early wireless communication fingerprinting techniques leverage the implementation characteristics of wireless network interface card (WNIC) hardware [11] or device-driver [16, 23]. However, the fingerprinting target is WNIC instead of physical device. These techniques also require the observer to be in the wireless range of the target device in order for the technique to work. Correspondingly, Kohno et al. introduced a passive physical device fingerprinting method that exploited the minute deviations in the clock skews to derive a clock cycle pattern as the device identity [19]. The analysis is not readily applicable to fingerprinting the semantic type of IoT devices.

State-of-the-art solutions for device-type identification in small scale networks rely on supervised machine learning with various traffic features [29, 22, 24]. GTID [29] extracts device signatures from the packet inter-arrival times (IATs), which are used to train an Artificial Neural Network (ANN) to identify device type. The device identification process requires several hours of traffic for signature generation. Moreover, solely relying on packet IATs makes it susceptible to spoofing attack where sophisticated attacker could emulate the IAT pattern of a different device. The authors of [22] design a device type detection technique that classifies encrypted link-layer traffic using random forest classifier. The technique only targets wireless devices, demanding passive eavesdropping using specialized radios. Similarly, Meidan et al. [24] performed IoT device type identification by applying random forest classifier to features extracted from TCP sessions.They only achieve acceptable accuracy through classification of 20 consecutive TCP sessions, while our method achieves high accuracy on single-flow classification.

Motivated by network security, IoT Sentinel [26] builds up a classifier on device fingerprints extracted from the burst of network traffic generated during the initial setup phase of the device. After assessing the vulnerability of the identified device type, security rules are enforced to constrain the communications of vulnerable devices. One limitation of IoT Sentinel is that it only operates

when a device is first introduced to a network. DIoT [27] uses unsupervised learning to classify devices into device types based on passive fingerprinting of periodic background traffic of IoT devices. For each device type, Gated recurrent unit (GRU) is used to establish the normal communication profile and subsequently detect anomalies in communication patterns. The fingerprinting strategy of DIoT is subject to deterioration since it merely relies on the periodicity inherent in background traffic. Furthermore, only an abstract device type is identified instead of the semantic type.

Another avenue of research centers on Internet-wide detection of IoT devices. Shodan [6] is the first search engine for discovering Internet-connected devices. Internally it uses Nmap to identify the application and services of an online device. Censys [14] employs banner-grabbing to gather device-specific information from the application-layer responses, and identifies devices based on a database of matching rules. Fingerprinting with Shodan and Censys demands cumbersome manual efforts for devising the matching rules. Recently, Feng et al. developed a search engine named ARE [15] for automatic device discovery and annotation in large scale. Device rules are built by correlating application-layer response data from IoT devices with the product descriptions (e.g., the device type and vendor) in relevant websites. The active probing performed by these techniques could be detected and defeated by sophisticated attackers through obfuscation. Moreover, the application layer data may not be readily available from banner grabbing. In contrast, our approach can automatically detect IoT device type using deep learning based classification.

Network Traffic Analysis. Network traffic analysis has been applied to various applications such as intrusion detection [36] and app identification [34]. These applications employ classical machine learning classifiers with different features extracted from the raw traffic (e.g., packet header, payload and statistics). For example, time-series features (packet lengths and inter-arrival times) are used for mobile application service usage classification [17]. Recent studies even achieve high malware detection accuracy on encrypted traffic using the plain text data contained in the TLS handshake [8]. These features are instructive for our passive traffic classification based IoT device fingerprinting. We perform fine-grained characterization of IoT devices and explore the power of a wide-range of features for IoT device identification.

9 Conclusions

This paper proposed a novel data-driven approach for automated and accurate fingerprinting of IoT device types. Our fingerprinting method relies on passive classification of potentially encrypted IoT flows. We first performed an in-depth empirical study of real-world IoT traffic, based on which we identify a variety of useful data features that could accurately characterize IoT device communications. Leveraging these features, we have developed a deep learning based classification model for IoT device fingerprinting. Using a real-world IoT dataset, our evaluation results demonstrate that the proposed method can achieve $\sim 99\%$

accuracy in IoT device-type identification based on single network flow classification.

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