PINGPONG: Packet-Level Signatures for Smart Home Device Events

Rahmadi Trimananda, Janus Varmarken, Athina Markopoulou, Brian Demsky University of California, Irvine {rtrimana, jvarmark, athina, bdemsky}@uci.edu

Abstract—Smart home devices are vulnerable to passive inference attacks based on network traffic, even in the presence of encryption. In this paper, we present PINGPONG, a tool that can automatically extract packet-level signatures for device events (e.g., light bulb turning ON/OFF) from network traffic. We evaluated PINGPONG on popular smart home devices ranging from smart plugs and thermostats to cameras, voice-activated devices, and smart TVs. We were able to: (1) automatically extract previously unknown signatures that consist of simple sequences of packet lengths and directions; (2) use those signatures to detect the devices or specific events with an average recall of more than 97%; (3) show that the signatures are unique among hundreds of millions of packets of real world network traffic; (4) show that our methodology is also applicable to publicly available datasets; and (5) demonstrate its robustness in different settings: events triggered by local and remote smartphones, as well as by homeautomation systems.

I. Introduction

Modern smart home devices are seeing widespread adoption. They typically connect to the Internet via the home Wi-Fi router and can be controlled using a smartphone or voice assistant. Although most modern smart home devices encrypt their network traffic, recent work has demonstrated that the smart home is susceptible to passive inference attacks [3], [10]–[13], [19], [29], [44], [45]. An eavesdropper may use characteristics of the network traffic generated by smart home devices to infer the device type and activity, and eventually user behavior. However, existing passive inference techniques have limitations. Most can only identify the device type and whether there is device activity (an event), but not the exact type of event or command [10]-[13], [29], [44], [45]. Others only apply to a limited number of devices from a specific vendor [19], or need more information from other protocols (e.g., Zigbee/Z-Wave) [3], [53] and the application source code [53]. Inference based on traffic volume analysis can be prevented by traffic shaping [3], [10]. Finally, many of these attacks assume that IP traffic is sniffed upstream from the home router, while the scenario where a local attacker sniffs encrypted Wi-Fi traffic has received less attention [10], [23].

In this paper, we experiment with a diverse range of smart home devices, namely 19 popular Wi-Fi and Zigbee devices (12 of which are the most popular smart home devices on

This is the technical report of the paper Packet-Level Signatures for Smart Home Devices published at Network and Distributed Systems Security (NDSS) Symposium 2020 23-26 February 2020, San Diego, CA, USA Amazon) from 16 popular vendors, including smart plugs, light bulbs, thermostats, home security systems, etc. During our analysis of the network traffic that these devices generate, we observed that events on smart home devices typically result in communication between the device, the smartphone, and the cloud servers that contains pairs of packets with predictable lengths. A packet pair typically consists of a request packet from a device/phone ("PING"), and a reply packet back to the device/phone ("PONG"). In most cases, the packet lengths are distinct for different device types and events, thus, can be used to infer the device and the specific type of event that occurred. Building on this observation, we were able to identify new packet-level signatures (or signatures for short) that consist only of the lengths and directions of a few packets in the smart home device traffic. In this paper, we show that these signatures: (1) can be extracted in an automated and systematic way without prior knowledge of the device's behavior; (2) can be used to infer fine-grained information, e.g., event types; (3) correspond to a variety of different events (e.g., "toggle ON/OFF" and "Intensity"/"Color"); and (4) have a number of advantages compared to prior (e.g., statistical, volume-based) approaches. More specifically, this paper makes the following contributions.

New Packet-Level Signatures. We discover new IoT device signatures that are simple and intuitive: they consist of short sequences of (typically 2-6) packets of specific lengths, exchanged between the device, the smartphone, and the cloud. The signatures are effective:

- They detect event occurrences with an average recall of more than 97%, surpassing the state-of-the-art techniques (see Sections II and V-B).
- 2) They are unique: we observe a low false positive rate (FPR), namely 1 false positive per 40 million packets in network traces with hundreds of millions of packets (see Section V-C).
- 3) They characterize a wide range of devices: (i) we extract signatures for 18 out of the 19 devices we experimented with, including the most popular home security devices such as the Ring Alarm Home Security System and Arlo Q Camera (see Section V-A); (ii) we extract signatures for 21 additional devices from a public dataset [39], including more complex devices, *e.g.*, voice-command devices, smart TVs, and even a fridge (see Section V-F).
- 4) They are robust across a diverse range of settings: (i) we extract signatures both from testbed experiments and publicly available datasets; and (ii) we trigger events in different ways, *i.e.*, using both a local and a remote smartphone, and using a home automation system.

- 5) They can be extracted from both unencrypted and encrypted traffic.
- 6) They allow quick detection of events as they rely only on a few packet lengths and directions, and do not require any statistical computation.

Automated Extraction of Packet-Level Signatures. We present PINGPONG, a methodology and software tool that: (1) automates the extraction of packet-level signatures without prior knowledge about the device, and (2) detects signatures in network traces and real network traffic. For signature extraction, PINGPONG first generates training data by repeatedly triggering the event, for which a signature is desired, while capturing network traffic. Next, PINGPONG extracts request-reply packet pairs per flow ("PING-PONG"), clusters these pairs, and post-processes them to concatenate pairs into longer sequences where possible. Finally, PINGPONG selects sequences with frequencies close to the number of triggered events as the final signatures. The signature detection part of PINGPONG leverages the simplicity of packet-level signatures and is implemented using simple state machines. PINGPONG's implementation and datasets are made available at [48].

The remainder of this paper is structured as follows. Section II outlines related work and puts PINGPONG in perspective. Section III presents the threat model (including two distinct adversaries: a WAN sniffer and a Wi-Fi sniffer), our experimental setup, and an illustrative example of packet-level signatures in smart plugs. Section IV presents the design of the PINGPONG system, including extraction and detection of signatures. Section V presents the evaluation of PINGPONG, using our own testbed experiments, as well as several external—publicly available—datasets. Section VI presents an in-depth discussion on possible defenses against packet-level signatures. Section VII concludes and outlines directions for future work.

II. RELATED WORK

Table I summarizes the properties of PINGPONG and compares it to the other IoT traffic analysis approaches.

Network Signatures for IoT devices. A growing body of work uses network traffic (metadata) analysis to characterize the type and activity of IoT devices. A series of papers by Apthorpe *et al.* [10]–[13] use traffic volume/shape-based signatures to infer IoT device activity, but cannot always determine the exact type of the event. Furthermore, the signatures corresponding to different traffic shapes are intuitive, but not automatically extracted. The authors propose stochastic traffic padding (STP) to mitigate volume-based inference attacks.

HomeSnitch [33] by OConnor *et al.* identifies IoT activity using a key observation that is similar to ours, *i.e.*, the client (the IoT device) and the server take turns in a request-reply communication style. HomeSnitch and PINGPONG both exclude IP addresses, port numbers, and DNS information from their event inference methodologies, but differ in terms of the granularity of the features they use: HomeSnitch uses statistics derived from the entire client-server dialog, whereas PINGPONG considers the direction and length of each individual packet. Interestingly, the most important feature used in HomeSnitch is the average number of bytes sent from the IoT device to the server per turn. This result aligns with the

						c Signatures		
	Vol.	Nest		hine Lear		ZigBee/	PING	
	+DNS	device	[33]	[3]	[44]	Z-Wave	Pong	
	based	[19]			[45]	device		
	[10]-					[53]		
	[13]							
		(1) Signatu	re can de	tect			
Device	√	√	√	√	√	√	\checkmark	
type								
Event	×	√	√	√	×	√	✓	
type								
		(2)	Applicab	ility to de	evices			
> 15	×	X	√	√	√	×	\checkmark	
Models								
1		(3) Obse	rvation p	oints/thre	at mode	İs		
LAN	×	√	√	√	√	N/A	\checkmark	
WAN	√	×	×	×	×	N/A	√	
Wi-Fi	√	×	×	√	×	N/A	√	
		(4)	Signature	characte	ristics			
Feat.	Traffic	TCP	13,	(795)	12	Packet	Packet	
	vol.,	conn.	ADU	197		length	length	
	DNS	size,				& dir.	& dir.	
		proto.						
Inter-	√	X	√	×	×	√	√	
pretable								
Auto.	×	×	√	√	√	√	√	
Extract.								
'	(5) Resilient against defenses							
VPN	X	×	×	×	×	N/A	\checkmark	
Traffic	×	×	×	×	×	N/A	√	
shaping								

TABLE I. PINGPONG'S PROPERTIES VS. ALTERNATIVE APPROACHES $(\sqrt{\ } = \text{Yes}; \times = \text{No}).$

main observation of this paper, *i.e.*, packet lengths of individual requests (and replies) uniquely identify device events.

A recent paper by Ren *et al.* [39] presents a large-scale measurement study of IoT devices and reveals how these devices operate differently in the US and the UK with respect to Internet endpoints contacted, exposure of private information, etc. We use that dataset to evaluate our methodology in Section V-F. The paper also presents a classifier that can infer event types spanning many device categories; this, however, is not the focus of the paper. Other well-known measurement studies and publicly available IoT network traffic datasets include YourThings [5], [6] and [45], which we use in our evaluation in Section V-C.

Other papers consider specific types of devices or protocols. Copos *et al.* [19] analyze network traffic of the Nest Thermostat and Nest Protect (only) and show that the thermostat's transitions between the *Home* and *Auto Away* modes can be inferred. Other work [3], [53] focus on Zigbee/Z-Wave devices and leverage specialized Zigbee/Z-Wave sniffers.

Most event inference techniques rely on machine learning [29], [44], [45] or statistical analysis of traffic time series [3], [19], [33], [39]. Limitations of these approaches include: the inability to differentiate event *types* [29], [44], [45] (*e.g.*, distinguishing ON from OFF), and lack of resistance to traffic shaping techniques [3], [19], [33], [39] such as [10]. On the other hand, our work identifies simple packet exchange(s) between the device/smartphone and the cloud that uniquely identify event types. At the same time, PINGPONG's classification performance (recall of more than 97%) is better than most statistical approaches: [3] reported 90% accuracy, [19] reported 88% and 67% accuracy, and [39] reported some F1 scores as

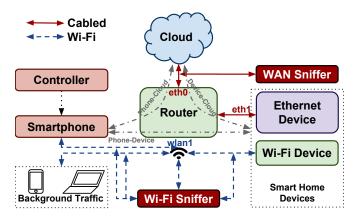


Fig. 1. Our experimental setup for studying smart home devices. "Wi-Fi Device" is any smart home device connected to the router via Wi-Fi (e.g., Amazon and WeMo plugs). "Ethernet Device" is any smart home device connected to the router via Ethernet (e.g., SmartThings hub that relays the communication of Zigbee devices). Smart home device events may result in communication between Phone-Cloud, Device-Cloud, or Phone-Device. There may also be background traffic from additional computing devices in the home.

low as 0.75. Unsupervised learning techniques may be hard to interpret, especially for large feature sets (*e.g.*, 197 features in [3]). PINGPONG also uses clustering to identify reoccurring packet pairs, but provides an intuitive interpretation of those pairs: they correspond to a request and the subsequent reply.

Network Traffic Analysis beyond IoT. There is a large body of work in the network measurement community that uses traffic analysis to classify applications and identify anomalies [26], [27], [32], attacks [20], or malware [8], [37]. There has also been a significant amount of work on fingerprinting techniques in the presence of encryption for web browsing [14], [17], [18], [21], [24], [25], [28], [30], [35], [36], [50], and variable bit-rate encodings for communication [51], [52] and movies [42]. For these examples, the underlying protocols are well understood, while PINGPONG can work with (and is agnostic to) any arbitrary, even proprietary, application-layer protocol.

Defenses. Related to profiling and fingerprinting is also the body of work on defenses that obfuscate traffic signatures. Examples include [31], [36] that use packet padding and traffic injection techniques to prevent website fingerprinting. In Table I, we mention two general defense approaches: (1) *traffic shaping* that refers broadly to changing the shape of traffic over time; and (2) *VPN* that brings multiple benefits such as encryption (that our signatures survive), and multiplexing of several flows. We partly evaluate these defenses (see Appendix C). A VPN also provides a natural place to implement additional defenses (*e.g.*, packet padding, which is discussed in Section VI).

III. PROBLEM SETUP

In this section, we first present our threat model. Then, we present the smart home environment and the passive inference attacks we consider. We also discuss a key insight we obtained from manually analyzing network traffic from the simplest devices—smart plugs. The packet sequences we observed in smart plugs inspired the PINGPONG methodology for automatically extracting signatures.

No.	Device Name	Model Details
1.	Amazon plug	Amazon Smart Plug
2.	WeMo plug	Belkin WeMo Switch
3.		Belkin WeMo Insight Switch
4.	Sengled light bulb	Sengled Element Classic
5.		Philips Hue white
6.	LiFX light bulb	LiFX A19
7.	Nest thermostat	Nest T3007ES
8.	Ecobee thermostat	Ecobee3
9.	Rachio sprinkler	Rachio Smart Sprinkler Controller
		Generation 2
10.	Arlo camera	Arlo Q
11.	Roomba robot	iRobot Roomba 690
12.	Ring alarm	Ring Alarm Home Security System
13.	TP-Link plug	TP-Link HS-110
14.	D-Link plug	D-Link DSP-W215
15.	D-Link siren	D-Link DCH-S220
16.	TP-Link light bulb	TP-Link LB-130
17.	SmartThings plug	Samsung SmartThings Outlet (2016
		model)
18.	Kwikset lock	Kwikset SmartCode 910
19.	Blossom sprinkler	Blossom 7 Smart Watering Controller

TABLE II. THE SET OF SMART HOME DEVICES CONSIDERED IN THIS PAPER. DEVICES HIGHLIGHTED IN GREEN ARE AMONG THE MOST POPULAR ON AMAZON.

A. Threat Model

In this paper, we are concerned with the network traffic of smart home devices leaking private information about smart home devices and users. Although most smart home devices encrypt their communication, information can be leaked by traffic metadata such as the lengths and directions of these encrypted packets.

We consider two different types of adversaries: a WAN sniffer and a Wi-Fi sniffer. The adversaries differ in terms of the vantage point where traffic is inspected and, thus, what information is available to the adversary. The WAN sniffer monitors network traffic in the communication between the home router and the ISP network (or beyond) [10]-[13]. This adversary can inspect the IP headers of all packets, but does not know the device MAC addresses to identify which device has sent the traffic. We assume a standard home network that uses NAT: all traffic from the home is multiplexed onto the router's IP address. Examples of such adversaries include intelligence agencies and ISPs. The Wi-Fi sniffer monitors encrypted IEEE 802.11 traffic, and has not been as widely studied [10], [23]. We assume that the Wi-Fi sniffer does not know the WPA2 key, and thus only has access to the information sent in clear text the MAC addresses, packet lengths, and timing information. As packets are encrypted, the Wi-Fi sniffer does not have access to network and transport layer information.

For both adversaries, we assume that the adversary knows the type of the smart home device that they wish to target and passively monitor. Thus, they can train the system on another device of the same type offline, extract the signature of the device, and perform the detection of the signature on the traffic coming from the smart home they target. We assume that the devices encrypt their communication and thus neither adversary has access to the clear-text communication.

B. Smart Home Environment and Experimental Testbed

Experimental Testbed. Figure 1 depicts our experimental setup, which resembles a typical smart home environment.

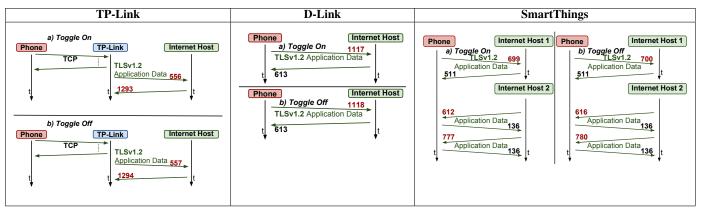


TABLE III. PACKET-LEVEL SIGNATURES OF TP-LINK, D-LINK, AND SMARTTHINGS SMART PLUGS OBSERVABLE BY THE WAN SNIFFER. THE NUMBERS REPRESENT PACKET LENGTHS, WITH RED INDICATING THAT THE LENGTH IS DIFFERENT FOR ON VS. OFF, AND THE ARROWS REPRESENT PACKET DIRECTIONS.

We experiment with 19 widely-used smart home devices from 16 different vendors (see Table II). We attempted to select a set of devices with a wide range of functionality—from plugs to cameras. They are also widely used: these devices are popular and they come from well-known vendors. The first 12 (highlighted in green) are the most popular on Amazon [7]: (1) each received the most reviews for its respective device type and (2) each had at least a 3.5-star rating—they are both popular and of high quality (e.g., the Nest T3007ES and Ecobee3 thermostats are the two most-reviewed with 4-star rating for thermostats). Some devices are connected to the router via Wi-Fi (e.g., the Amazon plug) and others through Ethernet. The latter includes the SmartThings, Sengled, and Hue hubs that relay communication to/from Zigbee/Z-Wave devices: the SmartThings plug, Kwikset doorlock, Sengled light bulb, and Hue light bulb.

Each smart home device in Figure 1 is controlled from the smartphone using its vendor's official Android application. In Figure 1, the smartphone is connected to a local network, which the devices are also connected to. When the smartphone is connected to a remote network, only the Device-Cloud communication is observable in the local network—the smartphone controls a device by communicating with its vendor-specific cloud, and the cloud relays the command to the device. The controller represents the agent that operates the smartphone to control the smart home device of interest. This may be done manually by a human (as in Section III-C) or through software (as in Section IV). Additionally, there are other computing devices (e.g., laptops, tablets, phones) in the house that also generate network traffic, which we refer to as "Background Traffic". The router runs OpenWrt/LEDE [34], a Linux-based OS for network devices, and serves as our vantage point for collecting traffic for experiments. We run topdump on the router's WAN interface (eth0) and local interfaces (wlan1 and eth1) to capture Internet traffic as well as local traffic for all Wi-Fi and Ethernet devices. We use the testbed to generate training data for each device, from which we in turn extract signatures (Section V-A). In Section V-B, the same testbed is used for testing, i.e., to detect the presence of the extracted signatures in traffic generated by all the devices as well as by other computing devices (background traffic).

Communication. Smart home device events may result in communication between three different pairs of devices, as

depicted in Figure 1: (1) the smartphone and the smart home device (*Phone-Device*); (2) the smart home device and an Internet host (*Device-Cloud*), and (3) the smartphone and an Internet host (*Phone-Cloud*). The idea behind a passive inference attack is that network traffic on any of these three communication paths may contain unique traffic signatures that can be exploited to infer the occurrence of events.

C. Motivating Case: Smart Plugs

As an illustrative example, let us discuss our manual analysis of 3 smart plugs: the TP-Link plug, the D-Link plug, and the SmartThings plug. Data for the manual analysis was collected using the setup in Figure 1. For each device, we toggled it ON, waited for approximately one minute, and then toggled it OFF. This procedure was repeated for a total of 3 ON and 3 OFF events, separated by one minute in between. Timestamps were manually noted for each event. The PCAP files logged at the router were analyzed using a combination of scripts and manual inspection in Wireshark.

New Observation: Packet Pairs. We identified the traffic flows that occurred immediately after each event and observed that certain pairs of packets with specific lengths and directions followed each ON/OFF event: the same pairs consistently showed up for all events of the same type (e.g., ON), but were slightly different across event types (ON vs. OFF). The pairs were comprised of a *request* packet in one direction, and a *reply* packet in the opposite direction. Intuitively, this makes sense: if the smart home device changes state, this information needs to be sent to (request), and acknowledged by (reply), the cloud server to enable devices that are not connected to the home network to query the smart home device's current state. These exchanges resemble the ball that moves back and forth between players in a game of pingpong, which inspired the name for our software tool.

Table III illustrates the observed packet exchanges. For the TP-Link plug, we observed an exchange of 2 TLS Application Data packets between the plug and an Internet host where the packet lengths were 556 and 1293 when the plug was toggled ON, but 557 and 1294 for OFF. We did not observe any pattern in the D-Link plug's own communication. However, for ON events, the controlling smartphone would always send a request packet of length 1117 to an Internet host and receive a reply

packet of length 613. For OFF, these packets were of lengths 1118 and 613, respectively. Similarly for the SmartThings plug, we found consistently occurring packet pairs in the smartphone's communication with two different Internet hosts where the lengths of the request packets were different for ON and OFF events. Thus, this request-reply pattern can occur in the communication of any of the three pairs: Phone-Device, Device-Cloud, or Phone-Cloud (see Figure 1).

Key Insight. This preliminary analysis indicates that each type of event is uniquely identified by the exchange of pairs (or longer sequences) of packets of specific lengths. To the best of our knowledge, this type of network signature has not been observed before, and we refer to it as a *packet-level signature*.

IV. PINGPONG DESIGN

The key insight obtained from our manual analysis in Section III-C was that unique sequences of packet lengths (for packet pairs or longer packet sequences) typically follow simple events (e.g., ON vs. OFF) on smart plugs, and can potentially be exploited as signatures to infer these events. This observation motivated us to investigate whether: (1) more smart home devices, and potentially the smartphones that control them as well, exhibit their own unique packet-level sequences following an event, (2) these signatures can be learned and automatically extracted, and (3) they are sufficiently unique to accurately detect events. In this section, we present the design of PINGPONG—a system that addresses the above questions with a resounding YES!

PINGPONG automates the collection of training data, extraction of packet-level signatures, and detection of the occurrence of a signature in a network trace. PINGPONG has two components: (1) training (Section IV-A), and (2) detection (Section IV-B). Figure 2 shows the building blocks and flow of PINGPONG on the left-hand side, and the TP-Link plug as an example on the right-hand side. We use the latter as a running example throughout this section.

A. Training

The training component is responsible for the extraction of packet-level signatures for a device the attacker wants to profile and attack. It consists of 5 steps (see Figure 2).

Data Collection. The first step towards signature generation is to collect a *training set* for the device. A training set is a network trace (a PCAP file) that contains the network traffic generated by the device and smartphone as a result of events; this trace is accompanied by a text file that contains the set of event timestamps.

PINGPONG partially automates training set collection by providing a shell script that uses the Android Debug Bridge (adb) [9] to issue touch inputs on the smartphone's screen. The script is run on a laptop that acts as the controller in Figure 1. The script is tailored to issue the sequence of touch events corresponding to the events for which a training set is to be generated. For example, if a training set is desired for a smart plug's ON and OFF events, the script issues a touch event at the screen coordinates that correspond to the respective buttons in the user interface of the plug's official Android app. As device vendors may choose arbitrary positions for the

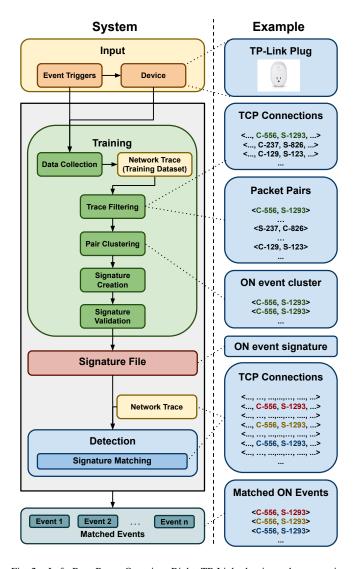


Fig. 2. Left: PINGPONG Overview. Right: TP-Link plug is used as a running example throughout this section.

buttons in their respective Android applications, and since the feature sets differ from device to device, the script must be manually modified for the given device. The script issues the touch sequence corresponding to each specific event n times, each separated by m seconds. The results reported in this paper use n=50 or n=100 depending on the event type (see Section V-A). The script also outputs the current timestamp to a file on the laptop when it issues an event. To collect a training set, we do the following: (1) start tepdump on the router's interfaces; (2) start the script; (3) terminate tepdump after the n-th event has been issued. This leaves us with a set of PCAP files and event timestamps, which constitute our raw training set.

We base our signature generation on the traces collected from the router's local interfaces as they are the vantage points that provide the most comprehensive information: they include both local traffic and Internet traffic. This allows PINGPONG

 $^{^{1}}$ We selected m=131 seconds to allow sufficient time such that there is no overlap between events. Section V-G provides more explanation for this choice with respect to other parameters.

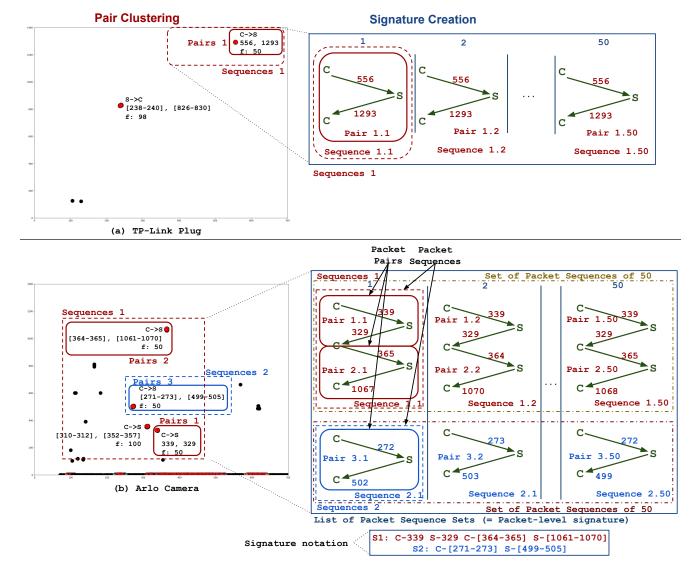


Fig. 3. Pair clustering and signature creation for 2 extreme cases—TP-Link plug has the simplest signature with only 1 pair (see our initial findings in Table III). The Arlo camera has a more complex signature with 1 sequence of 2 pairs and 1 sequence of 1 pair. The left subfigure, in every row, depicts the packet lengths in one packet pair (P_{c_1} , P_{c_2}). Notation: C->S means a pair where the first packet's direction is Client-to-Server and the second packet's direction is server-to-client, and vice versa for S->C; f: 50 means that the pair appears in the clustering with a *frequency of 50*; Signature notation shows a summary of 2 sets of 50 instances of packet sequences. Example: C->S 556, 1293 f: 50 means that the pair of packets with lengths 556 (client-to-server) and 1293 (server-to-client) appear 50 times in the cluster.

to exhaustively analyze all network packets generated in the communications between the device, smartphone, and Internet hosts on a per device basis. As signatures are based entirely on packet lengths and directions, signatures present in Internet traffic (*i.e.*, Device-Cloud and Phone-Cloud traffic) are applicable on the WAN side of the router, despite being extracted from traces captured within the local network

Trace Filtering. Next, PINGPONG filters the collected raw training set to discard traffic that is unrelated to a user's operation of a smart home device. All packets, where neither the source nor destination IP matches that of the device or the controlling smartphone, are dropped. Additionally, all packets that do not lie within a time window t after each timestamped event are discarded. We selected t=15 seconds to allow sufficient time for all network traffic related to the event to complete. We also performed a sensitivity study that confirmed

this was a conservative choice (see Section V-G).

PINGPONG next reassembles all TCP connections in the filtered trace. Given the set of reassembled TCP connections, we now turn our attention to the packets P that carry the TCP payload. For TLS connections, P is limited further to only be the subset of packets that are labeled as "Application Data" in the unencrypted TLS record header [41]. By only considering packets in P, we ensure that the inherently unpredictable control packets (e.g., TCP ACKs and TLS key negotiation) do not become part of the signature as P only contains packets with application layer payload.

We next construct the set P' by forming packet pairs from the packets in P (see Definition IV.1). This is motivated by the following observation: the deterministic sequence of packets that make up packet-level signatures often stem from a request-reply exchange between the device, smartphones, and

some Internet hosts (see Section III-C). Furthermore, since a packet pair is the simplest possible pattern, and since longer patterns (*i.e.*, packet sequences—see Definition IV.2) can be reconstructed from packet pairs, we look for these packet pairs in the training set. For the TP-Link plug example in Figure 2, PINGPONG reassembles <..., C-556, S-1293, ...>, <..., C-237, S-826, ...>, etc. as TCP connections. Then, PINGPONG extracts <C-556, S-1293>, <C-237, S-826>, etc. as packet pairs.

Definition IV.1. Packet Pair. Let P_c be the ordered set of packets with TCP payload that belong to TCP connection c, let P_{c_i} denote the i-th packet in P_c , and let C and S each denote client-to-server and server-to-client packet directions, respectively, where a client is a smartphone or a device. A packet pair p is then $p = (C - P_{c_i}, S - P_{c_{i+1}})$ or $p = (S - P_{c_i}, C - P_{c_{i+1}})$ iff P_{c_i} and $P_{c_{i+1}}$ go in opposite directions. Otherwise, if P_{c_i} and $P_{c_{i+1}}$ go in the same direction, or if P_{c_i} is the last packet in P_c , the packet pair $p = (C - P_{c_i}, \min)$ or $p = (S - P_{c_i}, \min)$ is formed, and packet $P_{c_{i+1}}$, if any, is paired with packet $P_{c_{i+2}}$.

Pair Clustering. After forming a set of packet pairs, relevant packet pairs (*i.e.*, those that consistently occur after an event) must next be separated from irrelevant ones. This selection also needs to take into account that the potentially relevant packet pairs may have slight variations in lengths. Since we do not know in advance the packet lengths in the pairs, we use an unsupervised learning algorithm: DBSCAN [22].

DBSCAN is provided with a distance function for comparing the similarity of two packet pairs, say p_1 and p_2 . The distance is maximal if the packet directions are different, e.g., if p_1 is comprised of a packet going from a local device to an Internet host followed by a packet going from an Internet host to a local device, while p_2 is comprised of a packet going from an Internet host to a local device followed by a packet going from a local device to an Internet host. If the packet directions match, the distance is simply the Euclidean distance between the two pairs, *i.e.*, $\sqrt{(p_1^1 - p_2^1)^2 + (p_1^2 - p_2^2)^2}$, where p_i^i refers to the packet length of the *i*-th element of pair j. DBSCAN's parameters are ϵ and minPts, which specify the neighborhood radius to consider when determining core points and the minimum number of points in that neighborhood for a point to become a core point, respectively. We choose $\epsilon = 10$ and minPts = |n - 0.1n|, where n is the total number of events. We allow a slack of 0.1n to minPts to take into account that event-related traffic could occasionally have missing pairs, for example caused by the phone app not responding to some of the automated events. We study the sensitivity of PINGPONG parameter values in Section V-G.

Figure 3(a) illustrates the pair clustering process for TP-Link plug. There are 50 ON and 50 OFF actions, and there must be at least 45 ($n=50 \implies \text{minPts} = \lfloor 50-0.1 \times 50 \rfloor = 45$) similar packet pairs to form a cluster. Two clusters are formed among the data points, *i.e.*, those with frequencies f: 50 and f: 98, respectively. Since these two clusters contain similar packet pairs that occur during t, this indicates with high confidence that the packets are related to the event.

Signature Creation. Given the output produced by DBSCAN, PINGPONG next drops all clusters whose frequencies are not in the interval $[\lfloor n-0.1n \rfloor, \lceil n+0.1n \rceil]$ in order to only include in the signature those clusters whose frequencies align closely with the number of events n. Intuitively, this step is to deal with *chatty devices*, namely devices that communicate continuously/periodically while not generating events. Consequently, PINGPONG only picks the cluster Pairs 1 with frequency 50 for the TP-Link plug example in Figure 3 as a signature candidate since 50 is in $[\lfloor n-0.1n \rfloor, \lceil n+0.1n \rceil] = [45,55]$ when n=50, whereas 98 is not. As a pair from this cluster occurs exactly once during t, there is high confidence that the pair is related to the event.

PINGPONG next attempts to concatenate packet pairs in the clusters so as to reassemble the longest packet sequences possible (see Definition IV.2), which increases the odds that a signature is unique. Naturally, packet pair concatenation is only performed when a device has more than one cluster. This is the case for the Arlo camera, but not the TP-Link plug. Packet pairs in clusters x and y are concatenated iff for each packet pair p_x in x, there exists a packet pair p_y in y such that p_x and p_y occurred consecutively in the same TCP connection. If there are more pairs in y than in x, the extra pairs of y are simply dropped. The result is referred to as a set of packet sequences (see Definition IV.3) and is considered for further concatenation with other clusters if possible.

Definition IV.2. Packet Sequence. A packet sequence s is formed by joining packet pairs p_1 and p_2 iff p_1 and p_2 are both in P_c (same TCP connection) and the packets in p_1 occur immediately before the packets in p_2 in P_c . Note that the packet sequence s resulting from joining p_1 and p_2 can be of length 2, 3, or 4, depending on whether or not the second element of p_1 and/or p_2 is nil.

Definition IV.3. Set of Packet Sequences. A set of packet sequences S is a set of similar packet sequences. Two packet sequences s_1 and s_2 are similar and thus belong to the same set S iff they (1) contain the same number of packets, (2) the packets at corresponding indices of s_1 and s_2 go in the same direction, and (3) the Euclidean distance between the packet lengths at corresponding indices of s_1 and s_2 is below a threshold—packet lengths in packet sequences inherit the slight variations that stem from packet pairs.

Figure 3(b) shows how pair clustering produces 3 clusters around the pairs <C-339, S-329> (*i.e.*, cluster Pairs 1), <C-[364-365], S-[1061-1070]> (*i.e.*, cluster Pairs 2), and <C-[271-273], S-[499-505]> (*i.e.*, cluster Pairs 3) for the Arlo camera. The notation C-[l_1-l_2] or S-[l_1-l_2] indicates that the packet length may vary in the range between l_1 and l_2 . Each pair from cluster Pairs 1 and each pair from cluster Pairs 2 are then concatenated into a sequence in Sequences 1 (a set of packet sequences) as they appear consecutively in the same TCP connection, *i.e.*, Pair 1.1 with Pair 2.1, Pair 1.2 with Pair 2.2, ..., Pair 1.50 with Pair 2.50. The cluster Pairs 3 is finalized as the set Sequences 2 as its members appear in different TCP connections than the

members of Sequences 1. Thus, the initial 3 clusters of packet pairs are reduced to 2 sets of packet sequences. For the TP-Link plug, no concatenation is performed since there is only a single cluster, Pairs 1, which is finalized as the set Sequences 1.

Finally, PINGPONG sorts the sets of packet sequences based on the timing of the sets' members to form a list of packet sequence sets (see Definition IV.4). For example, for the Arlo camera, this step produces a list in which the set Sequences 1 precedes the set Sequences 2 because there is always a packet sequence in Sequences 1 that precedes a packet sequence in Sequences 2. The purpose of this step is to make the temporal order of the sets of packet sequences part of the final signature. If no such order can be established, the set with the shorter packet sequences is discarded. Manual inspection of some devices suggests that the earlier sequence will often be the control command sent from an Internet host followed by the device's acknowledgment of the command, while the later sequence will stem from the device initiating communication with some other Internet host to inform that host about its change in status.

Definition IV.4. List of Packet Sequence Sets. A list of packet sequence sets is a list that contains sets of packet sequences that are sorted based on the occurrence of the set members in time. Set S_x goes before set S_y iff for each sequence s_x in S_x , there exists a sequence s_y in S_y that occurred after s_x within t.

Signature Validation. Before finalizing the signature, we validate it by running the detection algorithm (see Section IV-B) against the raw training set that was used to generate the signature. If PINGPONG detects at most n events, and the timestamps of detected events match the timestamps for events recorded during training, the signature is finalized as a valid packet-level signature (see Definition IV.5) and stored in a signature file. A signature can fail this check if it detects more events than the actual number of events in the training set (i.e., false positives). This can happen if the packet sequences in the signature frequently appear outside t.

Definition IV.5. Packet-level Signature. A packet-level signature is then a list of packet sequence sets that has been validated and finalized.

Signature File. A signature file stores a packet-level signature. Figure 3 shows that the TP-Link plug signature consists of 50 instances of packet sequences in set Sequences 1, but only one instance will be used during detection since all 50 are identical. Figure 3(b) shows the signature file (on the right-hand side) for the Arlo camera. It is a list that orders the two sets of packet sequences, Sequences 1 and Sequences 2. Sequences 1 is comprised of 50 packet sequences, each comprised of two packet pairs. Sequences 2 is comprised of another 50 packet sequences, each comprised of a single packet pair. Since the sequences vary slightly in each set, all unique variations are considered during detection.

B. Detection

For signature detection, PINGPONG treats a network trace as a stream of packets and presents each individual packet to

a set of state machines. A state machine is maintained for each packet sequence of the signature for each flow, i.e., TCP connection for the WAN sniffer or layer-2 flow for the Wi-Fi sniffer. A packet is only presented to the state machines associated with the flow that the packet pertains to. A state machine advances to its next state if the packet matches the next packet (in terms of length and direction) in the modeled packet sequence. The state machines respond differently to packets that do not match the expected next packet depending on whether detection is applied at layer-2 or layer-3. For layer-2, such packets are simply ignored, whereas for layer-3 such packets cause the state machine to discard the current partial match. When a state machine reaches its terminal state, the packet sequence match is reported to a secondary module. This module waits for a packet sequence match for each packet sequence of the signature and verifies the inter-sequence timing constraints before finally declaring a signature match. Please see Appendix A for a more detailed explanation of the detection.

V. EVALUATION

In this section, we present the evaluation of PINGPONG. In Section V-A, we show that PINGPONG automatically extracted event signatures for 18 devices as summarized in Table IV-11 of which are the most popular devices on Amazon (see Table II). In Section V-B, we used the extracted signatures to detect events in a trace collected from a realistic experiment on our smart home testbed. Section V-C discusses the results of negative control experiments: it demonstrates the uniqueness of the PINGPONG signatures in large (i.e., with hundreds of millions of packets), publicly available, packet traces from smart home and office environments. Section V-D discusses the results of our experiments when devices are triggered remotely from a smartphone and via a home automation service. Section V-E shows the uniqueness of signatures for devices from the same vendor. Section V-F discusses our findings when we used PINGPONG to extract signatures from a public dataset [39]. Finally, Section V-G discusses the selection and sensitivity of the parameters used to extract signatures.

A. Extracting Signatures from Smart Home Devices

Training Dataset. In order to evaluate the generalizability of packet-level signatures, we first used PINGPONG to automate the collection of training sets (see Section IV-A) for all 19 smart home devices (see Table II). Training sets were collected for every device under test, individually without any background traffic (see Figure 1). The automation script generated a total of 100 events for the device. For events with binary values, the script generated n=50 events for each event type (e.g., 50 ON and 50 OFF events). For events with continuous values, the script generated n=100 events (e.g., 100 intensity events for the Sengled light bulb).

Results Summary. For each training set, we used PINGPONG to extract packet-level signatures (see Section IV-A) for each event type of the respective device. In summary, PINGPONG extracted signatures from 18 devices (see Table IV). The signatures span a wide range of event types: binary (*e.g.*, ON/OFF) and non-binary (*e.g.*, light bulb intensity, color, etc.). Similar to our manual observation described in Section III-C,

Device	Event	Signature	Communication	Duration (ms) Min./Avg./Max.	Matc WAN Snif.	hing (Pe	r 100 Ev Wi-Fi Snif.	rents) FPR
	<u> </u>		Plugs		Siii.		Siii.	
Amazon plug	ON	S1: S-[443-445]	Device-Cloud	1,232 / 2,465 / 4,537	98	0	99	0
rimazon piag		S2: C-1099 S-235	Bevice cloud	1,232 / 2,103 / 1,33/				
	OFF	S1: S-[444-446]	†					
		S2: C-1179 S-235						
		S3: C-1514 C-103 S-235						
WeMo plug	ON/OFF	S1: PH-259 PH-475 D-246	Phone-Device	33 / 42 / 134	-	-	100	0
WeMo Insight plug	ON/OFF	S1: PH-259 PH-475 D-246	Phone-Device	32 / 39 / 97	-	-	99	0
TP-Link plug	ON	S1: C-556 S-1293	Device-Cloud	75 / 85 / 204	99	0	_	_
TP-LIIIK plug	OFF	S1: C-557 S-[1294-1295]	Device-Cloud	13 / 83 / 204	99	U	-	-
	ON	S1: PH-112 D-115	Phone-Device	225 / 325 / 3,328	_	_	99	0
	ON	S2: C-556 S-1293	&	223 1 323 1 3,326	_	_		0
	ON	S1: PH-112 D-115	Device-Cloud					
	ON	S2: C-557 S-[1294-1295]	Device-cloud					
D-Link plug	ON/OFF	S1: S-91 S-1227 C-784	Device-Cloud	4 / 1,194 / 8,060	95	0	95	0
D-Link plug	ON/OFT	S2: C-1052 S-647	Device-Cloud	4 / 1,194 / 6,000	93	U	93	0
	ON	S1: C-[1109-1123] S-613	Phone-Cloud	35 / 41 / 176	98	0	98	0
	OFF	S1: C-[1110-1124] S-613	I none cloud	337 417 170	/6		/ /0	
SmartThings plug	ON	S1: C-699 S-511	Phone-Cloud	335 / 537 / 2,223	92	0	92	0
Smartinings plug	ON	S2: S-777 C-136	1 none-cloud	333 7 337 7 2,223	1 12	U)2	0
	OFF	S1: C-700 S-511	+					
	Off	S2: S-780 C-136						
	1		ht Bulbs					
Sengled light bulb	ON	S1: S-[217-218] C-[209-210]	Device-Cloud	4,304 / 6,238 / 8,145	97	0		T -
Sengica fight build	ON	S2: C-430	Device-cloud	4,304 / 0,238 / 6,143	"	U	_	
		S3: C-466						
	OFF	S1: S-[217-218] C-[209-210]	+					
	011	S2: C-430						
		S3: C-465						
	ON	S1: C-211 S-1063	Phone-Cloud	4,375 / 6,356 / 9,132	93	0	97	0
		S2: S-1277						
	OFF	S1: C-211 S-1063 S-1276	†					
	Intensity	S1: S-[216-220]	Device-Cloud	16 / 74 / 824	99	2	-	-
		C-[208-210]						
	Intensity	S1: C-[215-217]	Phone-Cloud	3,916 / 5,573 / 7,171	99	0	99	0
		S-[1275-1277]						
Hue light bulb	ON	S1: C-364	Device-Cloud	11,019 / 12,787 /	-	-	-	-
_		S2: D-88	&	14,353				
	OFF	S1: C-365	Phone-Device					
		S2: D-88						
TP-Link light bulb	ON	S1: PH-198 D-227	Phone-Device	8 / 77 / 148	-	-	100	4
	OFF	S1: PH-198 D-244						
	Intensity	S1: PH-[240-242] D-[287-289]	Phone-Device	7 / 84 / 212	-	-	100	0
	Color	S1: PH-317 D-287	Phone-Device	6 / 89 / 174	-	-	100	0
			ermostats					
Nest thermostat	Fan ON	S1: C-[891-894] S-[830-834]	Phone-Cloud	91 / 111 / 1,072	93	0	93	1
	Fan OFF	S1: C-[858-860] S-[829-834]						
Ecobee thermostat	HVAC Auto	S1: S-1300 C-640	Phone-Cloud	121 / 229 / 667	100	0	99	0
	HVAC OFF	S1: C-1299 C-640						
	Fan ON	S1: S-1387 C-640	Phone-Cloud	117 / 232 / 1,776	100	0	100	0
	Fan Auto	S1: C-1389 C-640						
			rinklers					
Rachio sprinkler	Quick Run	S1: S-267 C-155	Device-Cloud	1,972 / 2,180 / 2,450	100	0	100	0
	Stop	S1: C-496 C-155 C-395						
	Standby/Active	S1: S-299 C-155 C-395	Device-Cloud	276 / 690 / 2,538	100	0	100	0
Blossom sprinkler	Quick Run	S1: C-326	Device-Cloud	701 / 3,470 / 8,431	96	0	96	0
		S2: C-177 S-505	1					
	Stop	S1: C-326						
		S2: C-177 S-458						
		S3: C-238 C-56 S-388	<u> </u>					
	Quick Run	S1: C-649 S-459 C-574 S-507	Phone-Cloud	70 / 956 / 3,337	93	0	93	0
		S2: S-[135-139]	1					
	Stop	S1: C-617 S-431	<u></u>	101 / 10 / /				
	Hibernate	S1: C-621 S-493	Phone-Cloud	121 / 494 / 1,798	95	0	93	0
	Active	S1: C-622 S-494						
	1	S2: S-599 C-566 S-554 C-566			1	1	l	1

Device	Event	Signature	Communication	Matc	Matching (Per 100 Events)			
				Min./Avg./Max.	WAN	FPR	Wi-Fi	FPR
					Snif.		Snif.	
		Home Secu	rity Devices					
Ring alarm	Arm	S1: S-99 S-254 C-99	Device-Cloud	275 / 410 / 605	98	0	95	0
		S-[181-183] C-99						
	Disarm	S1: S-99 S-255 C-99						
		S-[181-183] C-99						
Arlo camera	Stream ON	S1: C-[338-339] S-[326-329]	Phone-Cloud	46 / 78 / 194	99	2	98	3
		C-[364-365] S-[1061-1070]						
		S2: C-[271-273] S-[499-505]						
	Stream OFF	S1: C-[445-449] S-442						
D-Link siren	ON	S1: C-1076 S-593	Phone-Cloud	36 / 37 / 65	100	0	98	0
	OFF	S1: C-1023 S-613						
Kwikset door lock	Lock	S1: C-699 S-511	Phone-Cloud	173 / 395 / 2,874	100	0	100	0
		S2: S-639 C-136						
	Unlock	S1: C-701 S-511						
		S2: S-647 C-136						
	'	Otl	ners					
Roomba robot	Clean	S1: S-[1014-1015] C-105	Phone-Cloud	123 / 2,038 / 5,418	91	0	94	0
		S-432 C-105						
	Back-to-station	S1: S-440 C-105						
		S-[1018-1024] C-105						
				Average	97.05	0.18	97.48	0.32

TABLE IV. SMART HOME DEVICES FOUND TO EXHIBIT PHONE-CLOUD, DEVICE-CLOUD, AND PHONE-DEVICE SIGNATURES. PREFIX PH INDICATES PHONE-TO-DEVICE DIRECTION AND PREFIX D INDICATES DEVICE-TO-PHONE DIRECTION IN SIGNATURE COLUMN.

we again see that these events are identifiable by the requestreply pattern.

Table IV presents the signatures that PINGPONG identified.² Each line in a signature cell represents a packet sequence set, and the vertical positioning of these lines reflects the ordering of the packet sequence sets in the signature (see Section IV-A for the notation).

PINGPONG performed well in extracting signatures: it has successfully extracted packet-level signatures that are observable in the device's Phone-Cloud, Device-Cloud, and Phone-Device communications (see Table IV). Although the traffic is typically encrypted using TLSv1.2, the event still manifests itself in the form of a packet-level signature in the Phone-Cloud or Device-Cloud communication. PINGPONG also extracted signatures from the Phone-Device communication for some of the devices. These signatures are extracted typically from unencrypted local TCP/HTTP communication between the smartphone and the device.

Smart Plugs. PINGPONG extracted signatures from all 6 plugs: the Amazon, WeMo, WeMo Insight, TP-Link, D-Link, and SmartThings plugs. The Amazon, D-Link, and SmartThings plugs have signatures in the Phone-Cloud or Device-Cloud communication, or both. The TP-Link plug has signatures in both the Device-Cloud and Phone-Device communications. Both the WeMo and WeMo Insight plugs have signatures in the Phone-Device communication. In general, the signatures allow us to differentiate ON from OFF except for the WeMo, WeMo Insight, TP-Link plugs' Phone-Device communication, and D-Link plug's Device-Cloud communication (see Table IV).

Light Bulbs. PINGPONG extracted signatures from 3 light bulbs: the Sengled, Hue, and TP-Link light bulbs. The Sengled light bulb has signatures in both the Phone-Cloud and Device-Cloud communications. The Hue light bulb has signatures in both Device-Cloud and Phone-Device communications. The TP-Link light bulb has signatures only in the Phone-Device communication. Table IV shows that PINGPONG also extracted signatures for events other than ON and OFF: Intensity and Color.

Thermostats. PINGPONG extracted signatures for both the Nest and Ecobee thermostats. Both thermostats have Phone-Cloud signatures. The signatures allow us to differentiate Fan ON/OFF/Auto events. The Ecobee thermostat's signatures also leak information about its HVAC Auto/OFF events.

Sprinklers. PINGPONG extracted signatures from both the Rachio sprinkler and Blossom sprinkler. Both sprinklers have signatures in both the Device-Cloud and Phone-Cloud communications. The signatures allow us to differentiate Quick Run/Stop and Standby/Hibernate/Active events.

Home Security Devices. A highlight is that PINGPONG extracted signatures from home security devices. Notably, the Ring alarm has signatures that allow us to differentiate Arm/Disarm events in the Device-Cloud communication. The Arlo camera has signatures for Stream ON/OFF events, the D-Link siren for ON/OFF events, and the Kwikset lock for Lock/Unlock events in the Phone-Cloud communication.

Roomba robot. Finally, PINGPONG also extracted signatures from the Roomba robot in the Phone-Cloud communication. These signatures allow us to differentiate Clean/Backto-station events.

Signature Validity. Recall that signature validation rejects a signature candidate whose sequences are present not only in the time window *t*, but also during the subsequent idle period (see Section IV-A). We saw such a signature candidate for one device, namely the LiFX light bulb. PINGPONG captured

² Phone-Device signatures are observable only by the Wi-Fi sniffer. The Sengled light bulb's Device-Cloud signatures are sent by the Zigbee hub to the cloud through the Ethernet interface; thus, they are not observable by the Wi-Fi sniffer. The Hue light bulb has unique signatures; they consist of a pair, in which one is a Device-Cloud packet coming from the Zigbee hub to the cloud—this is observable only by the WAN sniffer since the hub is an Ethernet device—and the other one is a Phone-Cloud packet—this is observable only by the Wi-Fi sniffer; thus we did not use the signatures to perform detection since they partially belong to both adversaries.

a signature candidate that is present also in the idle period of the TCP communication and then rejected the signature during the validation phase. Manual inspection revealed that the LiFX light bulb uses unidirectional UDP communication (*i.e.*, no request-reply pattern) for events.

B. Smart Home Testbed Experiment

Testing Dataset. To evaluate the effectiveness of packet-level signatures in detecting events, we collected a separate set of network traces and used PINGPONG to perform detection on them. We used the setup in Section III-B to collect one dataset for every device. Our smart home setup consists of 13 of the smart home devices presented in Table II: the WeMo plug, WeMo Insight plug, Hue light bulb, LiFX light bulb, Nest thermostat, Arlo camera, TP-Link plug, D-Link plug, D-Link siren, TP-Link light bulb, SmartThings plug, Blossom sprinkler, and Kwikset lock. This fixed set of 13 devices was our initial setup—it gives us the flexibility to test additional devices without changing the smart home setup and needing to rerun all the experiments, yet still includes a variety of devices that generate background traffic. While collecting a dataset, we triggered events for the device under test. At the same time, we also connected the other 12 devices and turned them ON before we started the experiment—this allows the other devices to generate network traffic as they communicate with their cloud servers. However, we did not trigger events for these other devices. For the other 6 devices (the Amazon plug, Sengled light bulb, Ecobee thermostat, Rachio sprinkler, Roomba robot, and Ring alarm), we triggered events for the device under test while having all the 13 devices turned on. To generate additional background traffic as depicted in Figure 1, we set up 3 general purpose devices: a Motorola Moto g⁶ phone that would play a YouTube video playlist, a Google Nexus 5 phone that would play a Spotify song playlist, and an Apple MacBook Air that would randomly browse top 10 websites [4] every 10-500 seconds. We used this setup to emulate the network traffic from a smart home with many active devices.

Results Summary. Table IV presents the summary of our results (see column "**Matching**"). We collected a dataset with 100 events for every type of event—for binary events (*e.g.*, ON/OFF), we triggered 50 for each value. We performed the detection for both the WAN sniffer and Wi-Fi sniffer adversaries. For both adversaries, we have a negligible False Positive Rate (FPR) of 0.25 (0.18 for the WAN sniffer and 0.32 for the Wi-Fi sniffer) per 100 events for every event type.

C. Negative Control Experiment

If the packet-level signatures are to be used to detect events in traffic in the wild, they must be sufficiently unique compared to other traffic to avoid generating false positives. We evaluated the uniqueness of the signatures by performing signature detection on 3 datasets. The first 2 datasets serve to evaluate the uniqueness of the signatures among traffic generated by similar devices (*i.e.*, other smart home devices), while the third dataset serves to evaluate the uniqueness of the signatures among traffic generated by general purpose computing devices.

Dataset 1: UNSW Smart Home Traffic Dataset. The first dataset [45] contains network traces for 26 smart home devices that are *different* from the devices that we generated signatures for. The list can be found in [49]. The dataset is a collection of 19 PCAP files, with a total size of 12.5GB and a total of 23,013,502 packets.

Dataset 2: YourThings Smart Home Traffic Dataset. The second dataset [5], [6] contains network traces for 45 smart home devices. The dataset is a collection of 2,880 PCAP files, with a total size of 270.3GB and 407,851,830 packets. There are 3 common devices present in both YourThings and our set of 18 devices: the WeMo plug, Roomba robot, and TP-Link light bulb.

Dataset 3: UNB Simulated Office-Space Traffic Dataset. The third dataset is the Monday trace of the CICIDS2017 dataset [43]. It contains simulated network traffic for an office space with two servers and 10 laptops/desktops with diverse operating systems. The dataset we used is a single PCAP file of 10.82GB, with a total of 11,709,971 packets observed at the WAN interface.

False Positives. For datasets 1 and 3, we performed signature detection for all devices. For dataset 2, we only performed signature detection for the 15 of our devices that are *not* present in YourThings to avoid the potential for true positives. We used WAN sniffer detection for devices with Phone-Cloud and Device-Cloud signatures, and Wi-Fi sniffer detection for all devices.

WAN Sniffer. There were no false positives across 23,013,502 packets in dataset 1, 1 false positive for the Sengled light bulb across 407,851,830 packets in dataset 2, and 1 false positive for the Nest thermostat across 11,709,971 packets in dataset 3.

Wi-Fi Sniffer. PINGPONG detected some false positives due to its more relaxed matching strategy (see Section IV-B). The results show that the extracted packet-level signatures are unique: the average FPR is 11 false positives per signature across a total of 442,575,303 packets from all three datasets (i.e., an average of 1 false positive per 40 million packets).

Further analysis showed that signatures comprised of a single packet pair (e.g., the D-Link plug's Phone-Cloud signatures that only have one request and one reply packet) contributed the most to the average FPR—FPR is primarily impacted by signature length, not device type. Five 3-packet signatures generated 5, 7, 16, 26, and 33 false positives, while one 4-packet signature generated 2 false positives. There were also three outliers: two 4-packet signatures generated 46 and 33 false positives, and a 6-packet signature generated 18 false positives. This anomaly was due to PINGPONG using the range-based matching strategy for these signatures (see Appendix A). Furthermore, the average of the packet lengths for the signatures that generated false positives is less than 600 bytes: the packet lengths distribution for our negative datasets shows that there are significantly more shorter packets than longer packets.

D. Events Triggered Remotely

Our main dataset, collected using our testbed (see Section V-A), contains events triggered by a smartphone that

is part of the local network (*i.e.*, the smart home testbed). However, smart home devices can also be controlled remotely, using home automation frameworks or a remote smartphone. In this section, we summarize our results for these scenarios. Please see Appendix B for details.

Home Automation Experiment (IFTTT). We integrated IFTTT into our existing infrastructure for triggering device events. IFTTT provides support for 13 out of our 18 devices: no support was provided at the time of the experiment for the Amazon plug, Blossom sprinkler, Roomba robot, Ring alarm, and Nest thermostat. The main finding is that, from the supported 13 devices, PINGPONG successfully extracted Device-Cloud signatures for 9 devices and 12 event types.

Comparison of Device-Cloud Signatures. We also compared the Device-Cloud signatures of the TP-Link plug, the D-Link plug, and the Rachio sprinkler. Our results show that the majority of Device-Cloud signatures are the same or very similar across 3 different ways of triggering the devices: local smartphone, remote smartphone, and IFTTT.

E. Devices from the Same Vendor

Since the signatures reflect protocol behavior, a natural question to ask is whether devices from the same vendor, which probably run similar protocols, have the same signature. In our testbed experiment, we had already extracted signatures from 2 TP-Link devices: the TP-Link plug and TP-Link light bulb (see Table IV). We also acquired, and experimented with, 4 additional devices from TP-Link. We defer the detailed results to Table X. In summary, we found that packet-level signatures have some similarities (*e.g.*, the TP-Link two-outlet plug and TP-Link power strip have similar functionality and have packet lengths 1412B and 88B). However, they are still distinct across different device models and event types, even for devices with similar functionality (*e.g.*, the TP-Link plug, TP-Link two-outlet plug, and TP-Link power strip).

F. Public Dataset Experiment

In this section, we apply the PINGPONG methodology to a state-of-the-art, publicly available IoT dataset: the Mon(IoT)r dataset [39]. First, we show that PINGPONG successfully extracted signatures from new devices in this dataset, thus validating the generality of the methodology and expanding our coverage of devices. Then, we compare the signatures extracted from the Mon(IoT)r dataset to those extracted from our testbed dataset, for devices that were present in both.

The Mon(IoT)r Dataset. The Mon(IoT)r dataset [39] contains network traces from 55 distinct IoT devices.³ Each PCAP file in the dataset contains traffic observed for a single device during a short timeframe surrounding a single event on that device. Moreover, the authors provide timestamps for when they performed each event. As a result, we can merge all PCAP files for each device and event type combination into a single PCAP file, and directly apply PINGPONG to extract signatures, similarly to how we extracted signatures from the training set we collected using our testbed.

We only considered a subset of the 55 devices in the Mon(IoT)r dataset, due to a combination of limitations of the dataset and of our methodology. In particular, we did not apply PINGPONG to the following groups of devices in the Mon(IoT)r dataset: (1) 3 devices with nearly all PCAP files empty; (2) 6 devices with a limited number (three or less) of event samples; and (3) 13 devices that only communicate via UDP (PINGPONG's current implementation only considers TCP traffic). Next, we report results from applying PINGPONG to the remaining 33 devices in the Mon(IoT)r dataset. Out of those, 26 are exclusive to the Mon(IoT)r dataset, while seven are common across the Mon(IoT)r dataset and our testbed dataset.

Devices only in the Mon(IoT)r Dataset. We ran PINGPONG's signature extraction on the traces from the 26 new devices from the Mon(IoT)r dataset. PINGPONG successfully extracted signatures for 21 devices and we summarize those signatures in Table V.⁵ Some of these devices provide similar functionality as those in our testbed dataset (*e.g.*, bulbs, cameras). Interestingly, we were also able to successfully extract signatures for many new types of devices that we did not have access to during our testbed experiments. Examples include voice-activated devices, smart TVs, and even a fridge. This validates the generality of the PINGPONG methodology and greatly expands our coverage of devices.

There were also 5, out of 26, new devices that PINGPONG originally appeared to not extract signatures from. However, upon closer inspection of their PCAP files and PINGPONG's output logs, we observed that those devices did actually exhibit a new type of signature that we had not previously encountered in our testbed experiments: a sequence of packet pairs with the exact same pair of packet lengths for the same event. The default configuration of PINGPONG would have discarded the clusters of these packet pairs during the signature creation of the training phase (see Section IV-A), because the number of occurrences of these pairs is higher than (in fact a multiple of) the number of events. However, based on this intuitive observation, PINGPONG can easily be adapted to extract those signatures as well: it can take into account the timing of packet pairs in the same cluster instead of only across different clusters, and concatenate them into longer sequences. We note that these frequent packet pairs can be either new signatures for new devices, or can be due to periodic background communication. Unfortunately, the Mon(IoT)r dataset does not include network traces for idle periods (where no events are generated), thus we cannot confirm or reject this hypothesis.

Common Devices. We next report our findings for devices that are present in both the Mon(IoT)r dataset and in our own testbed dataset, referred to as common devices. There were already 6 common devices across the 2 datasets, and we acquired an additional device after consulting with the

³The paper [39] reports results from 81 physical devices, but 26 device models are present in both the US and the UK testbed, thus there are only 55 distinct models.

⁴We consider this to be too few samples to have confidence in the extracted signatures. In contrast, the traces for the remaining devices generally had 30–40 event samples for each device and event type combination.

 $^{^5}$ For some of the devices, we had to relax the training time window, *i.e.*, t=30s, because there is usually a gap of more than 20s from the provided timestamps to the appearance of event-related traffic. As a result, PINGPONG extracted longer signatures for certain devices, *e.g.*, the Lefun camera. Further, we also had to exclude some PCAP files that are empty or contain traffic that look inconsistent with the majority (*e.g.*, some only contain DNS or IGMP traffic)

Device	Event	Signature	Duration (ms)
		Cameras	
Amazon camera	Watch	S1: S-[627-634] C-[1229-1236]	203 / 261 / 476
Blink hub	Watch	S1: S-199 C-135 C-183 S-135	99 / 158 / 275
	Photo	S1: S-199 C-135 C-183 S-135	87 / 173 / 774
Lefun camera	Photo	S1: S-258 C-[206-210] S-386 C-206	17,871 / 19,032 / 20,358
		S2: C-222 S-198 C-434 S-446 C-462 S-194 C-1422 S-246 C-262	
		S3: C-182	
	Recording	S1: S-258 C-210 S-386 C-206	13,209 / 15,279 / 16,302
		S2: C-222 S-198 C-434 S-446 C-462 S-194	
	Watch	S1: S-258 C-210 S-386 C-206	14,151 / 15,271 / 16,131
		S2: C-222 S-198 C-434 S-446 C-462 S-194	
Microseven camera	Watch	S1: D-242 PH-118	1 / 5 / 38
ZModo doorbell	Photo	S1: C-94 S-88 S-282 C-240 / S1: S-282 C-240 C-94 S-88	1,184 / 8,032 / 15,127
Ziriodo dooroon	Recording	S1: C-94 S-88 S-282 C-240 / S1: S-282 C-240 C-94 S-88	305 / 7,739 / 15,137
	Watch	S1: C-94 S-88 S-282 C-240 / S1: S-282 C-240 C-94 S-88	272 / 7,679 / 15,264
	Water	Light Bulbs	27277,677713,201
Flex light bulb	ON/OFF	S1: PH-140 D-[346-347]	4 / 44 / 78
Tick light build	Intensity	S1: PH-140 D-346	4 / 18 / 118
	Color	S1: PH-140 D-340 S1: PH-140 D-346	4 / 12 / 113
Wink hub	ON/OFF	S1: PH-204 D-890 PH-188 D-113	43 / 55 / 195
WIIK HUD			
	Intensity Color	S1: PH-204 D-890 PH-188 D-113 S1: PH-204 D-890 PH-188 D-113	43 / 50 / 70 43 / 55 / 106
	Color		43 / 33 / 100
A 11 1	AII. ON/OFF	Voice Command Devices	90 / 152 / 10/
Allure speaker	Audio ON/OFF	S1: C-658 C-412	89 / 152 / 196
	Volume	S1: C-[594-602]	217 / 4,010 / 11,005
		S2: C-[92-100]	
Amazon Echo Dot	Voice	S1: C-491 S-[148-179]	1 / 23 / 61
	Volume	S1: C-[283-290] C-[967-979]	1,555 / 2,019 / 2,423
		S2: C-[197-200] C-[147-160]	
Amazon Echo Plus	Audio ON/OFF	S1: S-100 C-100	1 / 5 / 28
	Color	S1: S-100 C-100	1 / 4 / 18
	Intensity	S1: S-100 C-100	1 / 4 / 11
	Voice	S1: C-[761-767] S-437	1,417 / 1,871 / 2,084
		S2: C-172 S-434	
	Volume	S1: C-172 S-434	2 / 13 / 40
Amazon Echo Spot	Audio ON/OFF	S1: S-100 C-100	1 / 8 / 233
	Voice	S1: C-246 S-214	1,220 / 1,465 / 1,813
		S2: C-172 S-434	
	Volume	S1: C-246 S-214	1,451 / 1,709 / 1,958
		S2: C-172 S-434	
Google Home	Voice	S1: C-1434 S-136	9 / 61 / 132
	Volume	S1: C-1434 S-[124-151]	8,020 / 9,732 / 10,002
		S2: C-521 S-[134-135]	
Google Home Mini	Voice	S1: C-1434 S-[127-153]	1 / 29 / 112
C	Volume	S1: C-1434 S-[135-148]	5 / 47 / 123
Harman Kardon	Voice	S1: S-1494 S-277 C-1494	2.199 / 2.651 / 3.762
Invoke speaker		S2: S-159 S-196 C-1494	
of	Volume	S1: S-159 S-196 C-1418 C-1320 S-277	223 / 567 / 793
		S2: S-196 C-[404-406]	225 , 55, , , , , , ,
		Smart TVs	
Fire TV	Menu	S1: C-468 S-323	16 / 18 / 20
LG TV	Menu	S1: PH-204 D-1368 PH-192 D-117	43 / 90 / 235
Roku TV	Remote	S1: PH-163 D-[163-165]	578 / 1,000 / 1,262
NORU I V	Remote	S2: PH-145 D-410	37671,00071,202
		S2: PH-147 D-113	
Samsung TV	Monu	S1: PH-[237-242] D-274	2 / 7 / 15
Samsung 1 V	Menu	Other Types of Devices	2///13
Honoravall the	ON	S1: S-635 C-256 C-795 S-139 C-923 S-139	1 001 / 1 249 / 1 420
Honeywell thermostat	ON		1,091 / 1,248 / 1,420
	OFF	S1: S-651 C-256 C-795 S-139 C-923 S-139	96 / 102 / 122
T , 1 1	Set	S1: C-779 S-139	86 / 102 / 132
Insteon hub	ON/OFF	S1: S-491 C-623	76 / 100 / 1,077
		S2: C-784 C-234 S-379	
	_		
Samsung fridge	Set View Inside	S1: C-116 S-112 S1: C-116 S-112	177 / 185 / 185 177 / 197 / 563

TABLE V. SIGNATURES EXTRACTED FROM THE DEVICES ONLY IN THE MON(IOT)R [39] DATASET.

authors of the paper: the Blink camera. We excluded 2 common devices: (1) the Nest thermostat as it was tested for different event types; and (2) the Hue light bulb as it has a unique signature that PINGPONG cannot use to perform matching—it

is a combination of Device-Cloud (visible only to the WAN sniffer) and Phone-Device communications (visible only to the Wi-Fi sniffer). Table VI summarizes the results for the 5 remaining common devices. First, we report the complete

Device	Event	Signature	Duration (ms)	Matching			
			Min./Avg./Max./St.Dev.	WAN Sniffer	FPR	Wi-Fi Sniffer	FPR
WeMo Insight plug	ON/OFF	*S1: PH-475 D-246	29 / 33 / 112 / 9	-	-	98.75%	0
		† S1: PH-475 D-246	31 / 42 / 111 / 15	1			
Blink camera	Watch	*S1: C-331 S-299 C-139	267 / 273 / 331 / 8	100%	0	100%	0
		† S1: C-331 S-299 C-139	170 / 269 / 289 / 19				
	Photo	*S1: C-331 C-123 S-139 S-123 S-187 C-1467	281 / 644 / 1,299 / 348	97.37%	0	97.50%	0
		† S1: C-331 C-123 S-139 S-123 S-187 C-1467	281 / 742 / 2,493 / 745				
TP-Link plug	ON	*S1: C-592 S-1234 S-100	70 / 74 / 85 / 2	100%	0	-	-
(Device-Cloud)	OFF	*S1: C-593 S-1235 S-100					
	ON	†S1: C-605 S-1213 S-100	16 / 19 / 29 / 2	1			
	OFF	†S1: C-606 S-1214 S-100					
TP-Link plug	ON	*S1: PH-172 D-115	406 / 743 / 10,667 / 1,417	-	-	100%	0
(Phone-Device &		S2: C-592 S-1234 S-100					
Device-Cloud)	OFF	*S1: PH-172 D-115					
		S2: C-593 S-1235 S-100					
	ON	† S1: PH-172 D-115	197 / 382 / 663 / 165				
		S2: C-605 S-1213 S-100					
	OFF	† S1: PH-172 D-115					
		S2: C-606 S-1214 S-100					
Sengled light bulb	ON	*S1: S-[217-218] C-[209-210]	4,304 / 6,238 / 8,145 / 886	-	-	-	-
		S2: C-430					
		S3: C-466					
	OFF	*S1: S-[217-218] C-[209-210]					
		S2: C-430					
		S3: C-465					
	ON	† S1: S-219 C-210	354 / 2,590 / 3,836 / 859	1			
		S2: C-428					
		S3: C-[478-479]					
	OFF	† S1: S-219 C-210					
		S2: C-428					
		S3: C-[478-480]					
TP-Link light bulb	ON	*S1: PH-258 D-288	8 / 77 / 148 / 42	-	-	-	-
-	OFF	*S1: PH-258 D-305					
	ON	† S1: PH-258 D-227	17 / 92 / 224 / 46	1			
	OFF	† S1: PH-258 D-244					

TABLE VI. COMMON DEVICES IN THE MON(IOT)R AND OUR TESTBED EXPERIMENTS. * SIGNATURE: TRAINING ON OUR TESTBED. † SIGNATURE: TRAINING ON MON(IOT)R [39]. MATCHING: TRAINING ON TESTBED, DETECTION ON MON(IOT)R. THE NUMBER OF EVENTS VARY (AROUND 30-40) PER EVENT TYPE—THE RESULT IS PRESENTED IN % FOR CONVENIENCE.

signatures extracted from each dataset. The signatures reported in Table IV were obtained from data collected throughout 2018. For the WeMo Insight plug and TP-Link plug, we repeated our testbed data collection and signature extraction in December 2019 to facilitate a better comparison of signatures from the same devices across different points in time. Then, we compare the signatures extracted from the two datasets for the common devices: some of the signatures are identical and some are similar. Such a comparison provides more information than simply training on one dataset and testing on the other.

Identical Signatures. For the WeMo Insight plug and Blink camera, the signatures extracted from the Mon(IoT)r dataset and our dataset (December 2019) were identical. Since the signatures obtained from our own dataset do not have any variations in packet lengths, we used PINGPONG's exact matching strategy (see Section IV-B) to detect events in the Mon(IoT)r dataset, and we observed a recall rate of 97% or higher for both devices (see Table VI).

Similar Signatures. For the TP-Link plug and Sengled light bulb, the signatures extracted from the Mon(IoT)r dataset are slightly different from those extracted from our own dataset: some packet lengths at certain positions in the sequence are different (by a few and up to tens of bytes), and these differences appear to be consistent (i.e., all signatures from

both datasets appear to be completely deterministic as they do not contain packet length ranges). For example, the TP-Link plug's ON event is C-592 S-1234 S-100 in our experiment vs. C-605 S-1213 S-100 in Mon(IoT)r. To understand the cause of these discrepancies, we examined the TP-Link plug in further detail—between the two devices, its signatures exhibit the largest difference in packet lengths across datasets. Through additional experiments on the TP-Link plug, we identified that changes to configuration parameters (e.g., user credentials of different lengths) could cause the packet lengths to change. However, the packet lengths are deterministic for each particular set of user credentials.

For devices that exhibit this kind of behavior, an attacker must first train PINGPONG multiple times with different user credentials to determine to what extent these configuration changes affect the packet lengths in the signatures. Moreover, the signature matching strategy should not be exact, but must be relaxed to allow for small variations in packet lengths. To this end, we implemented *relaxed matching* that augments the matching strategies discussed in Section IV-B.⁶ We ran

 $^{^6}$ In relaxed matching, a delta equal to the greatest variation observed in packet lengths is applied to the packets that vary due to configuration changes. For the TP-Link plug, we observed that the first packets differ by 13B in the the Device-Cloud signatures from the two datasets (i.e., 13 = 605 - 592 = 606 - 593) and the second packets differ by 21B (i.e., 21 = 1234 - 1213 = 1235 - 1214), thus a delta of 21B is used.

PINGPONG with relaxed matching on the TP-Link plug with a delta of 21B, and successfully detected 100% of events. Furthermore, by performing the negative control experiments described in Section V-C, we verified that the increase in FPR due to relaxed matching is negiligible. For dataset 1, relaxed matching results in two FPs for the Wi-Fi sniffer. For dataset 3, relaxed matching results in seven FPs for the Wi-Fi sniffer and one FP for the WAN sniffer. In comparison, exact matching only produces one false positive for the Wi-Fi sniffer for dataset 3. We note that the total number of packets across these datasets is 440 million. However, relaxed matching may eliminate the ability to distinguish event types for signatures that only differ by a few bytes (*e.g.*, the packet lengths for the TP-Link plug's ON and OFF signatures differ by one byte).

Signature Evolution. We observed that some signatures change over time, presumably due to changes to the device's communication protocol. The WeMo Insight plug's signature changed slightly from our earlier dataset from 2018 (see Table IV) to our latest dataset collected in December 2019 (see Table VI): the first PH-259 packet is no longer part of the signature. Both of these datasets were collected using the same testbed with the same user accounts, but with different device firmware versions. Therefore, the change is probably due to changes in the communication protocol, introduced in firmware updates. This is further backed by the observation that the WeMo Insight plug's signature extracted from the Mon(IoT)r dataset (collected in April 2019) is identical to the signature extracted from our December 2019's dataset. This implies that there has been a protocol change between 2018 and April 2019, but the protocol has then remained unchanged until December 2019.

Similarly, the TP-Link light bulb's signature has changed slightly from our first to our second in-house dataset (see Tables IV and VI), and is also slightly different for the Mon(IoT)r dataset. The signatures from our 2018 dataset and those from the Mon(IoT)r dataset differ in the first packet (PH-198 vs. PH-258, an offset of 60 bytes), and the signatures from the Mon(IoT)r dataset and those from our December 2019 differ in the second packet (D-227 vs. D-288 and D-244 vs. 305, an offset of 61 bytes). Thus, we also suspect that there is a signature evolution due to firmware updates for the TP-Link light bulb. Signature evolution is a limitation of our approach, and is elaborated on in Section VII. Nevertheless, an attacker can easily overcome this limitation simply by repeating PINGPONG's training to extract the latest signatures from a device right before launching an attack.

G. Parameters Selection and Sensitivity

Clustering Parameters. We empirically examined a range of values for the parameters of the DBSCAN algorithm. We tried all combinations of $\epsilon \in \{1, 2, ..., 10\}$ and minPts $\in \{30, 31, ..., 50\}$. For those devices that exhibit no variation in their signature related packet lengths, e.g., the TP-Link plug, the output of the clustering remains stable for all values of ϵ and minPts < 50. For such devices, keeping ϵ at a minimum and minPts close to the number of events n reduces the number of noise points that become part of the resulting clusters. However, our experiments show that there is a tradeoff

in applying strict bounds to devices with more variation in their packet lengths (e.g., the D-Link plug), strict bounds can result in losing clusters that contain packet pairs related to events. For the D-Link plug, this happens if $\epsilon < 7$ and $\mathtt{minPts} > 47$. In our experiments, we used our initial values of $\epsilon = 10$ and $\mathtt{minPts} = 45$ (i.e., $\mathtt{minPts} = \lfloor n - 0.1n \rfloor$ with n = number of expected events) from our smart plugs experiment (i.e., the TP-Link plug, D-Link plug, and SmartThings plug) that allowed PINGPONG to produce the packet-level signatures we initially observed manually (see Section III-C). We then used them as default parameters for PINGPONG to analyze new devices and extracted packet-level signatures from 15 more devices.

Time Window and Signature Duration. We also measured the duration of our signatures—defined as the time between the first and the last packets of the signature. Table IV reports all the results. The longest signature duration measured is 9,132 ms (less than 10 seconds) for the Sengled light bulb's ON/OFF signatures from the Phone-Cloud communication. This justifies our choice of training time window t=15 seconds during trace filtering and signature validation (see Section IV-A). This conservative choice also provides slack to accommodate other devices that we have not evaluated and that may have signatures with a longer duration. This implies that events can be generated every 15 seconds or longer. We conservatively chose this duration to be 131 seconds to give ample time for an event to finish, and to easily separate false positives from true positives.

VI. POSSIBLE DEFENSES

There are several broad approaches that can obfuscate network traffic to defend against passive inference attacks that analyze network traffic metadata:

- 1) Packet padding adds dummy bytes to each packet to confuse inference techniques that rely on individual packet lengths, and less so volume. Packets can be padded to a fixed length (e.g., MTU) or with a random number of bytes.
- 2) *Traffic shaping* purposely delays packets to confuse inference techniques that rely on packet inter-arrival times and volume over time.
- 3) *Traffic injection* adds dummy packets in patterns that look similar (*e.g.*, have the same lengths, inter-arrival times or volume signature etc.) as the real events, thus hiding the real event traffic in a crowd of fake events.

The above approaches can be implemented in different ways and can also be combined (*e.g.*, on the same VPN). Since our signatures rely on unique sequences of individual packet lengths, packet padding is the most natural defense and therefore discussed in depth below. We defer discussion of traffic shaping and traffic injection to Appendix C. We first provide a brief overview of packet padding in the literature. We then discuss how packet padding may be implemented to obfuscate packet-level signatures. Finally, we evaluate the efficacy of packet padding for the TP-Link plug.

Packet Padding in the Literature. Packet padding has already been studied as a countermeasure for website fingerprinting [15], [16], [21], [28]. Liberatore and Levine [28] showed that padding to MTU drastically reduces the accuracy of a Jaccard coefficient based classifier and a naive Bayes classifier, both of which use a feature set very similar to packet-level

 $^{^{7}\}mbox{We}$ also repeated our experiments for the TP-Link light bulb to further understand this phenomenon.

signatures: a vector of <direction, packet length> tuples. Dyer et al. [21] later showed that such padding is less successful against more advanced classifiers, such as the support vector machine proposed by Panchenko et al. [36] that also considers coarse-grained features such as total traffic volume. Cai et al. [15], [16] improved [21] by providing a strategy to control traffic flow that better obfuscates the traffic volume as a result. Although applied in a different context, these prior works indicate that packet padding should successfully guard against a packet-level signature attack. The question then becomes where and how to implement the padding mechanism.

Possible Implementations. Next, we discuss the potential benefits and drawbacks of different packet padding implementations. We consider a VPN-based implementation, padding at the application layer, and TLS-based padding.

VPN. One option is to route traffic from the smart home devices and the smartphone through a VPN that pads outbound tunneled packets with dummy bytes and strips the padding off of inbound tunneled packets: a technique also considered in [10]. The smart home end of the VPN may be implemented either directly on each device and smartphone or on a middlebox, e.g., the home router. The former provides protection against both the WAN and Wi-Fi sniffers as the padding is preserved on the local wireless link, whereas the latter only defends against the WAN sniffer. However, an on-device VPN may be impractical on devices with limited software stacks and/or computational resources. The middlebox-based approach may be used to patch existing devices without changes to their software. Pinheiro et al. [38] provide an implementation in which the router is the client-side end of the VPN, and where the padding is added to the Ethernet trailer.

Application Layer and TLS. Another option is to perform the padding at the application layer. This has at least three benefits: (1) it preserves the padding across all links, thus provides protection against both the WAN and Wi-Fi sniffers; (2) it imposes no work on the end user to configure their router to use a VPN; and (3) it can be implemented entirely in software. An example is HTTPOS by Luo et al. [31], which randomizes the lengths of HTTP requests (e.g., by adding superfluous data to the HTTP header). One drawback of application layer padding is that it imposes extra work on the application developer. This may be addressed by including the padding mechanism in libraries for standardized protocols (e.g., OkHttp [47]), but a separate implementation is still required for every proprietary protocol. A better alternative is to add the padding between the network and application layers. This preserves the benefits of application layer padding highlighted above, but eliminates the need for the application developer to handle padding. As suggested in [21], one can use the padding functionality that is already available in TLS [40].

Residual Side-Channel Information. Even after packet padding is applied, there may still be other side-channels, *e.g.*, timing and packet directions, and/or coarse-grained features such as total volume, total number of packets, and burstiness, as demonstrated by [21]. Fortunately, timing information (*e.g.*, packet inter-arrival times and duration of the entire packet exchange) is highly location dependent (see the comparison of signature durations in Table VI), as it is impacted by the propagation delay between the home and the cloud, as well

as the queuing and transmission delays on individual links on this path. Exploiting timing information requires a much more powerful adversary: one that uses data obtained from a location close to the smart home under attack. The work of Apthorpe *et al.* on traffic shaping [13] and stochastic traffic padding (STP) [10] may aid in obfuscating timing, volume, and burstiness.

Efficacy of Packet Padding. The discussion has been qualitative so far. Next, we perform a simple test to empirically assess the efficacy of packet padding for the TP-Link plug.

Setup. We simulated padding to the MTU by post-processing the TP-Link plug testbed trace from Section V-B (50 ON and 50 OFF events, mixed with background traffic) using a simplified version of PINGPONG's detection that only considers the order and directions of packets, but pays no attention to the packet lengths. We focus on the WAN sniffer because it is the most powerful adversary: it can separate traffic into individual TCP connections and eliminate the confusion that arises from multiplexing. We used the TP-Link plug's two-packet signatures for ON and OFF events (see Table IV) as the Phone-Device communication is not visible on the WAN. We consider the packet padding's impact on transmission and processing delays to be negligible. We assume that the adversary uses all available information to filter out irrelevant traffic. Specifically, the adversary uses the timing information observed during training to only consider request-reply exchanges that comply with the signature duration.⁸ Moreover, since the TP-Link plug uses TLSv1.2 (which does not encrypt the SNI), the adversary can filter the trace to only consider TLS Application Data packets to the relevant TP-Link host(s) in the no-VPN scenarios.

VPN-Based Padding. To simulate VPN-based packet padding, we consider all packets in the trace as multiplexed over a single connection and perform signature detection on this tunnel. This results in a total of 193,338 positives, or, put differently, more than 1,900 false positives for every event. This demonstrates that VPN-based packet padding works well for devices with short signatures (e.g., a single packet pair).

TLS-Based Padding. From the training data, the adversary knows that the signature is present in the TP-Link plug's communication with events.tplinkra.com. To simulate TLS-based packet padding, we performed signature detection on the TLS Application Data packets of each individual TLSv1.2 connection with said host. As expected, this produced a total of 100 detected events, with no FPs. Intuitively, this is because the only TLS Application Data packets of these connections are exactly the two signature packets, and the device only communicates with this domain when an event occurs.

Hybrid. We next explore how multiplexing all of the TP-Link plug's traffic over a single connection affects the false positives

 $^{^8}t=0.204s \implies \lceil 0.204+0.1\times 0.204s \rceil = 0.224s$ (see Table IV and Appendix A)

(the plug communicates with other TP-Link hosts). This is conceptually similar to a VPN, but only tunnels application layer protocols and can be implemented in user space (without TUN/TAP support). To simulate such a setup, we filtered the trace to only contain IPv4 unicast traffic to/from the TP-Link plug, and dropped all packets that were not TLS Application Data. We then performed detection on the TLS Application Data packets, treating them as belonging to a single TLS connection. For this scenario, we observed 171 positives. While significantly better than TLS-based padding for individual TLS connections, the attacker still has a high probability (more than 50%) of guessing the occurrence of each event (but cannot distinguish ON from OFF).

Recommendations. Based on the above insights, we recommend VPN-based packet padding due to its additional obfuscation (encryption of the Internet endpoint and multiplexing of IoT traffic with other traffic) as TLS-based padding seems insufficient for devices with simple signatures and little background traffic. For more chatty devices, multiplexing all device traffic over a single TLS connection to a single server may provide sufficient obfuscation at little overhead.

VII. CONCLUSION AND DISCUSSION

Summary. We designed, implemented, and evaluated PING-PONG, a methodology for automatically extracting packet-level signatures for smart home device events from network traffic. Notably, traffic can be encrypted or generated by proprietary or unknown protocols. This work advances the state-of-the-art by: (1) identifying simple packet-level signatures that were not previously known; (2) proposing an automated methodology for extracting these signatures from training datasets; and (3) showing that they are effective in inferring events across a wide range of devices, event types, traces, and attack models (WAN sniffer and Wi-Fi sniffer). We have made PINGPONG (software and datasets) publicly available at [48]. We note that the new packet-level signatures can be used for several applications, including launching a passive inference attack, anomaly detection, etc. To deal with such attacks, we outlined a simple defense based on packet padding.

Current Limitations and Future Directions. PINGPONG has its limitations and can be extended in several directions.

First, in order to extract the signature of a new device, one must first acquire the device and apply PINGPONG to train and extract the corresponding packet-level signatures. This is actually realistic for an attacker with minimal side information, *i.e.*, one who knows what device they want to attack or who wants to distinguish between two different types of devices. One direction for future work is to extend PINGPONG by finding "similar" known behaviors for a new device, *e.g.*, via relaxed matching of known and unknown signatures.

Second, a signature may evolve over time, *e.g.*, when a software/firmware update changes a device's communication protocol. Whoever maintains the signature (*e.g.*, the attacker) needs to retrain and update the signature. We observed this phenomenon, for example, for the TP-Link plug. This can be handled by relaxed matching since the packet sequences tend to be mostly stable and only evolve by a few bytes (see Section V-F).

Third, there may be inherent variability in some signatures due to configuration parameters (*e.g.*, credentials and device IDs) that are sent to the cloud and may lead to slightly different packet lengths. In Section V-F, we saw that this variability is small: from a few to tens of bytes difference and only for some individual packets within a longer sequence. An attacker could train with different configuration parameters and apply relaxed matching when necessary (only on packets with length variations).

Other possible improvements include: profiling and subtracting background/periodic traffic during signature creation, and unifying the way we account for small variation in the signatures in the training and detection—PINGPONG currently supports range-based matching (see Appendix A) and relaxed matching as separate features. Another limitation is that our methodology currently applies only to TCP—not to UDP-based devices that do not follow the request-reply pattern.

Conclusion. We believe that the new packet-level signatures identified by PINGPONG are a simple, intuitive, and universal means for profiling IoT devices. However, we see PINGPONG only as a building block, which is part of a bigger toolbox for IoT network traffic analysis. We believe that it can and should be combined with other complementary ideas, *e.g.*, traffic shape/volume-based signatures, semi-supervised learning, etc.

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 $^{^9\}mathrm{We}$ envision that this could be implemented by maintaining a single TLS connection between the device and a single TP-Link endpoint, T, that would then carry all application layer messages, each prepended with an additional header that identifies the type and order of that particular request/response, and padded to MTU using TLS record padding. For each request, T would interpret its type based on the application layer header, and forward it to an appropriate backing server responsible for that part of the application logic (i.e., T is analogous to a load balancer).

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APPENDIX

A. Detection

PINGPONG's detection component determines if a packetlevel signature is present in a captured network trace, or realtime network traffic. The implementation differs slightly for the two adversaries described in Section III-A.

Layer-2 Information. The Wi-Fi sniffer has the disadvantage of only having access to layer-2 header information due to WPA2 encryption. This means that it cannot reconstruct TCP connections, but can only separate traffic into flows of packets exchanged between pairs of MAC addresses, referred to as *layer-2 flows*. On layer 2, the encryption added by WPA2 does not pad packet lengths. Thus, our signatures, extracted from TCP/IP traffic, can be directly mapped to layer 2 if the IEEE 802.11 radiotap header, frame header, the AES-CCMP IV and key identifier, and FCS are accounted for. In our testbed, these consistently add 80 bytes to the packet length.

Packet Sequence Matching. A state machine is maintained for each packet sequence of the signature for each flow, i.e., TCP connection for the WAN sniffer or layer-2 flow for the Wi-Fi sniffer. Each packet in the stream of packets is presented to the state machines associated with the flow that the packet pertains to. If the packet's length and direction match that of the packet for the next state, the state machine advances and records the packet. The detection algorithm operates differently for layer-2 and layer-3 detections when the packet does not match the expected next packet. For layer-2 detection (Wi-Fi sniffer), the packet is simply ignored, and the state machine remains in the same state. Out-of-order packets can in theory cause failures for our current layer-2 signature matching implementation. In practice, out-of-order packets occur rarely enough that they are unlikely to be a significant issue. There are other mitigating factors that further lower the likelihood of out-of-order packets posing a problem. Signatures that strictly follow the pingpong pattern do not provide an opportunity for their packets to be reordered. Out-of-order packets often result in TCP ACKs in the other direction that would cause retransmissions. Thus, another event packet would be seen right after the first one and the first one would be ignored. For layer-3 detection (WAN sniffer), the packet causes the state machine to discard any partial match—layer-3 detection does not deal with interleaving packets as it considers individual TCP connections and can filter out TCP retransmissions. When a state machine matches its first packet and advances to the next state, a new state machine is created for the same packet sequence, but in the initial state. This is to ensure that the state machine starts at the correct first packet, e.g., when a packet of that length appears in other traffic. To bound the number of active state machines, and to minimize the number of false positives resulting from retransmissions, any state machine that advances from state s to state s+1 replaces any existing state machine in state s+1 iff the last packet of the newly advanced state machine has a later timestamp than that of the existing state machine. Once a state machine reaches its terminal state, the set of recorded packets is reported as a sequence match.

Matching Strategies. For every packet in a sequence, there are two possible matching strategies: *exact* and *range-based* matching. In exact matching, the state machines only consider exactly those packet lengths that were observed during training

Dorries	Event	C:	Comm.	Dunati ()			ching (Per efense	r 100 Ev	vents) STP+VPN	
Device	Event	Signature	Comm.	Duration (ms) Min./Avg./Max.	WAN Snif.	FPR	Wi-Fi Snif.	FPR	WAN Snif.	FPR
			Plu				, J			
Amazon plug	ON OFF	S1: S-[443-445] S2: C-1099 S-235 S1: S-[444-446]	Device-Cloud	1,232 / 2,465 / 4,537	98	0	99	0	99	0
	011	S2: C-1179 S-235 S3: C-1514 C-103 S-235								
WeMo plug	ON/OFF	S1: PH-259 PH-475 D-246	Phone-Device	33 / 42 / 134	-	-	100	0	-	-
WeMo Insight plug	ON/OFF	S1: PH-259 PH-475 D-246	Phone-Device	32 / 39 / 97	-	-	99	0	-	-
TP-Link plug	ON OFF	S1: C-556 S-1293 S1: C-557 S-[1294-1295]	Device-Cloud	75 / 85 / 204	99	0	-	-	98	3
78	ON	S1: PH-112 D-115 S2: C-556 S-1293	Phone-Device &	225 / 325 / 3,328	-	-	99	0	-	-
	ON	S1: PH-112 D-115 S2: C-557 S-[1294-1295]	Device-Cloud							
D-Link plug	ON/OFF	S1: S-91 S-1227 C-784 S2: C-1052 S-647	Device-Cloud	4 / 1,194 / 8,060	95	0	95	0	95	0
	ON OFF	\$1: C-[1109-1123] S-613 \$1: C-[1110-1124] S-613	Phone-Cloud	35 / 41 / 176	98	0	98	0	98	0
Smart- Things	ON	S1: C-699 S-511 S2: S-777 C-136	Phone-Cloud	335 / 537 / 2,223	92	0	92	0	92	0
plug	OFF	S1: C-700 S-511 S2: S-780 C-136								
		5 2. 5 700 € 130	Light	Bulbs						
Sengled light bulb	ON	S1: S-[217-218] C-[209-210] S2: C-430 S3: C-466	Device-Cloud	4,304 / 6,238 / 8,145	97	0	-	-	97	0
buib	OFF	S1: S-[217-218] C-[209-210] S2: C-430								
	ON	S3: C-465 S1: C-211 S-1063 S2: S-1277	Phone-Cloud	4,375 / 6,356 / 9,132	93	0	97	0	96	1
	OFF	S1: C-211 S-1063 S-1276	-							
	Intensity	S1: S-[216-220] C-[208-210]	Device-Cloud	16 / 74 / 824	99	2	-	-	99	5
** "	Intensity	S1: C-[215-217] S-[1275-1277]	Phone-Cloud	3,916 / 5,573 / 7,171	99	0	99	0	98	2
Hue light bulb	ON OFF	S1: C-364 S2: D-88	Device-Cloud &	11,019 / 12,787 / 14,353	-	-	-	-	-	-
TD 1 :1-		S1: C-365 S2: D-88	Phone-Device	0 / 77 / 140			100	1		
TP-Link light bulb	ON OFF Intensity	S1: PH-198 D-227 S1: PH-198 D-244 S1: PH-[240-242] D-[287-289]	Phone-Device	8 / 77 / 148 7 / 84 / 212	-	-	100	0	-	-
	Color	S1: PH-317 D-287	Phone-Device Therm	6 / 89 / 174	-	-	100	0	-	-
Nest	Fan ON	S1: C-[891-894] S-[830-834]	Phone-Cloud	91 / 111 / 1,072	93	0	93	1	93	2
thermostat Ecobee	Fan OFF HVAC	S1: C-[858-860] S-[829-834] S1: S-1300 C-640	Phone-Cloud	121 / 229 / 667	100	0	99	0	99	0
thermostat	Auto HVAC OFF	S1: C-1299 C-640								
	Fan ON Fan Auto	S1: S-1387 C-640 S1: C-1389 C-640	Phone-Cloud	117 / 232 / 1,776	100	0	100	0	100	1
		1	Sprin				1		1	1
Rachio sprinkler	Quick Run Stop	S1: S-267 C-155 S1: C-496 C-155 C-395	Device-Cloud	1,972 / 2,180 / 2,450	100	0	100	0	100	1
	Standby/ Active	S1: S-299 C-155 C-395	Device-Cloud	276 / 690 / 2,538	100	0	100	0	100	0
Blossom sprinkler	Quick Run	S1: C-326 S2: C-177 S-505	Device-Cloud	701 / 3,470 / 8,431	96	0	96	0	96	3
	Stop	S1: C-326 S2: C-177 S-458 S3: C-238 C-56 S-388								
	Quick Run Stop	S1: C-649 S-459 C-574 S-507 S2: S-[135-139] S1: C-617 S-431	Phone-Cloud	70 / 956 / 3,337	93	0	93	0	93	0

						Mato	ching (Per	100 Ev	ents)	
Device	Event	Signature	Comm.	Duration (ms)		No D	efense		STP+	VPN
				Min./Avg./Max.	WAN Snif.	FPR	Wi-Fi Snif.	FPR	WAN Snif.	FPR
	Hibernate	S1: C-621 S-493	Phone-Cloud	121 / 494 / 1,798	95	0	93	0	93	1
	Active	S1: C-622 S-494								
		S2: S-599 C-566 S-554 C-566								
			Home Securit	y Devices						
Ring alarm	Arm	S1: S-99 S-254 C-99	Device-Cloud	275 / 410 / 605	98	0	95	0	95	0
		S-[181-183] C-99								
	Disarm	S1: S-99 S-255 C-99								
		S-[181-183] C-99								
Arlo	Stream ON	S1: C-[338-339] S-[326-329]	Phone-Cloud	46 / 78 / 194	99	2	98	3	97	4
camera		C-[364-365] S-[1061-1070]								
		S2: C-[271-273] S-[499-505]								
	Stream	S1: C-[445-449] S-442								
	OFF									
D-Link	ON	S1: C-1076 S-593	Phone-Cloud	36 / 37 / 65	100	0	98	0	97	0
siren	OFF	S1: C-1023 S-613								
Kwikset	Lock	S1: C-699 S-511	Phone-Cloud	173 / 395 / 2,874	100	0	100	0	100	0
door		S2: S-639 C-136								
lock	Unlock	S1: C-701 S-511								
		S2: S-647 C-136								
			Other	S						
Roomba	Clean	S1: S-[1014-1015] C-105	Phone-Cloud	123 / 2,038 / 5,418	91	0	94	0	94	1
robot		S-432 C-105								
	Back-to-	S1: S-440 C-105								
	station	S-[1018-1024] C-105								
				Average	97.05	0.18	97.48	0.32	96.77	1.09

TABLE VII. SMART HOME DEVICES FOUND TO EXHIBIT PHONE-CLOUD, DEVICE-CLOUD, AND PHONE-DEVICE SIGNATURES. PREFIX PH INDICATES PHONE-TO-DEVICE DIRECTION AND PREFIX D INDICATES DEVICE-TO-PHONE DIRECTION IN SIGNATURE COLUMN.

as valid. In the range-based matching strategy, the state machines allow the packet lengths to lie between the minimum and maximum packet lengths (plus a small delta) observed during training. As such, range-based matching attempts to accommodate packet sequences that have slight variations where all permutations may not have been observed during training. For range-based matching, the lower and upper bounds for each packet of a packet sequence are derived from the core points of the packet pair clustering (see Section IV-A). ϵ is then applied to these bounds analogous to the clustering technique used in the DBSCAN algorithm—we, therefore, consistently use the same $\epsilon = 10$. For example, for $\epsilon = 10$ and core points <C-338, S-541> and <C-339, S-542>, a state machine that uses range-based matching will consider clientto-server packets with lengths in [328, 349], and serverto-client packets with lengths in [531, 552] as valid.

Exact matching is used when no variations in packet lengths were observed during training, and range-based matching is used if variations in packet lengths were observed during training. However, range-based matching is not performed when the signature only consists of 2 packets and/or there is an overlap between the signatures that represent different types of events (*e.g.*, the D-Link plug's signatures for ON and OFF in Table IV) as range-based matching for 2-packet signatures has a high risk of generating many false positives.

Declaring a Signature Match. A sequence match does not necessarily mean that the full signature has been matched. Some signatures are comprised of multiple packet sequences and all of them have to be matched (*e.g.*, Arlo camera, see Section IV-A). Sequence matches are therefore reported to a secondary module that verifies if the required temporal constraints are in place, namely that the sequence match for packet sequence set *i* occurs *before* the sequence match for

packet sequence set i+1 and that the time between the first packet of the sequence match corresponding to packet sequence set 1 and the last packet of the sequence match corresponding to packet sequence set k (for a signature with k packet sequence sets) is below a threshold. A signature match is declared when all matching packet sequence sets occur within the duration $\lceil t+0.1t \rceil$ with t being the maximum observed signature duration (see Table IV).

Simultaneous Events. Finally, during signature matching, PINGPONG'S algorithm first separates incoming packets into different sets on a per device basis: individual TCP connections in the WAN sniffer matching, or individual substreams based on source/destination MAC addresses in the Wi-Fi sniffer matching. Since the devices we have seen only generate events sequentially, sequences that correspond to a certain event will also appear sequentially in the network trace: there will never be an overlap of events in a single device. If two devices or more generate events simultaneously, the corresponding sequences will be either in separate TCP connections for the WAN sniffer adversary or separate substreams for the Wi-Fi sniffer adversary: there will never be overlap of events generated by different devices. This also implies that changing the amount and types of background traffic (e.g., video or audio streaming) does not affect our signatures—other traffic will be in different TCP connections/substreams.

B. Events Triggered Remotely

Our main dataset, collected using our testbed (see Section V-A), contains events triggered by a smartphone that is part of the local network. However, smart home devices can also be controlled remotely, using home automation frameworks or a remote smartphone. In this section, we show that

Device	Event	Device-Cloud Signature	Duration (ms)	Matc	hing (Pe	r 100 Eve	nts)
			Min./Avg./Max.	WAN Sniffer	FPR	Wi-Fi Sniffer	FPR
	<u>'</u>	Plugs					
WeMo plug	ON/OFF	S1: S-146	226 / 345 / 2,236	100	0	100	0
337.34 T 11.1	OM	S2: C-210 S-134 S-286 C-294	216 / 252 / 452	00		0.4	
WeMo Insight plug	ON	S1: S-146 S2: C-210 S-134 S-286 C-294	216 / 253 / 473	99	0	94	0
	OFF	S1: S-146 S2: C-210 S-134 S-350 C-294					
TP-Link plug	ON	S1: C-592 S-1234 S-100	71 / 76 / 139	100	0	100	0
	OFF	S1: C-593 S-1235 S-100					
D-Link plug	ON/OFF	S1: C-256 S2: C-1020 S-647	269 / 750 / 6,364	93	1	93	1
		Light Bulbs					
Hue light bulb	ON	S1: S-[227-229] C-[857-859] C-365	37 / 44 / 76	99	1	-	-
	OFF	S1: S-[227-230] C-[857-860] C-366					
	Intensity	S1: S-[237-240] C-[895-899] S2: C-[378-379]	36 / 40 / 96	97	0	-	-
TP-Link light bulb	ON	S1: S-[348-349] C-[399-400]	11 / 15 / 78	100	0	100	0
	OFF	S1: S-[348-349] C-[418-419]					
	Intensity	S1: S-[438-442] C-[396-400]	12 / 16 / 53	100	0	99	0
	Color	S1: S-[386-388] C-[397-399]	12 / 17 / 60	99	0	97	0
		Others					
Rachio sprinkler	Quick Run	S1: S-267 C-155	1,661 / 2467 / 4,677	95	3	95	5
	Stop	S1: C-661					
		S2: C-155					
Arlo camera	Start Recording	S1: C-704 S-215	156 / 159 / 195	100	0	99	0
D-Link siren	ON	S1: S-[989-1005] C-616 S2: C-216	162 / 181 / 281	99	1	98	1
	-1		Average	98.4	0.5	97.5	0.7

TABLE VIII. DEVICE-CLOUD SIGNATURE IN 9 DEVICES TRIGGERED BY IFTTT HOME AUTOMATION.

Device	Event		Device-Cloud Signatures						
		Local-Phone	Remote-Phone	IFTTT					
TP-Link plug	ON	S1: C-592 S-1234 S-100	S1: C-592 S-1234 S-100	S1: C-592 S-1234 S-100					
	OFF	S1: C-593 S-1235 S-100	S1: C-593 S-1235 S-100	S1: C-593 S-1235 S-100					
D-Link plug	ON/OFF	S1: S-91 S-1227 C-784	S1: S-91 S-1227 C-784	S1: C-256					
		S2: C-1052 S-647	S2: C-1052 S-647	S2: C-1020 S-647					
Rachio sprinkler	Quick Run	S1: S-267 C-155	S1: S-267 C-155 C-837 C-448	S1: S-267 C-155					
	Stop	S1: C-496 C-155 C-395	S1: S-219 S-235 C-171 C-661 C-496 C-155 C-395	S1: C-661					
				S2: C-155					

TABLE IX. COMPARISON OF DEVICE-CLOUD SIGNATURES FOR THREE DEVICES (TP-LINK PLUG, D-LINK PLUG, AND RACHIO SPRINKLER) TRIGGERED IN THREE DIFFERENT WAYS: VIA (I) A LOCAL PHONE, (II) A REMOTE PHONE, AND (III) IFTTT HOME AUTOMATION.

even with such remote triggers, the Device-Cloud communication exhibits similar signatures, which can be extracted using PINGPONG.

Home Automation Experiment (IFTTT). In this section, we trigger events using the IFTTT (If-This-Then-That) home automation platform [1], which supports most of our devices. IFTTT is one of the most popular web-based home automation frameworks: in 2019 it provides around 700 services for 17 million users [46]. IFTTT allows users to set up automation rules that work in a *Trigger-Action* fashion. Each automation rule typically connects a trigger (*i.e.*, *This*) to an action (*i.e.*, *That*). The occurrence of the trigger causes the action to be performed by the framework. For example, "if motion is detected, then turn on the smart plug" [2].

In this experiment, we use IFTTT to trigger events. We integrate IFTTT into our existing infrastructure for triggering device events via Android widget button presses. For each event type, we develop an IFTTT rule that triggers the event using an Android button widget. For example, we set up a button widget to toggle ON the TP-Link plug: "if the widget

button is pressed, then turn on the smart plug". Then, we install the IFTTT app on our smartphone, log in to the app using our IFTTT account, and add the button widget onto the home screen of the smartphone. Then, instead of using the official Android app, we use the button widget to trigger events from the smartphone. The smartphone is connected to a different network than the smart home testbed network to simulate controlling the devices from a remote location.

For every device: (1) we use IFTTT to trigger events to collect a new training dataset, and we run PINGPONG to extract packet-level signatures from the Device-Cloud communication in this dataset; (2) we collect a new smart home testbed dataset (as in Section V-B, but using the IFTTT widget to trigger events), which we then use for testing, *i.e.*, to detect events by matching on the IFTTT signatures extracted from the aforementioned training dataset.

Signatures Found in Device-Cloud Communication. IFTTT provides support for 13 out of our 18 devices: no support was provided at the time of the experiment for the Amazon plug, Blossom sprinkler, Roomba robot, Ring alarm, and Nest

thermostat. The main finding is that, from the supported 13 devices, PINGPONG successfully extracts Device-Cloud signatures for nine devices and 12 event types, which are summarized in Table VIII. Three out of the nine supported devices (the TP-Link plug, the D-Link plug, and the Rachio sprinkler) already have Device-Cloud signatures when triggered by a local phone: the phone is connected to the smart home testbed, where the device is also connected to (see Table VII). Interestingly, six out of the nine supported devices have Device-Cloud signatures when triggered via IFTTT, but did not have Device-Cloud signatures when triggered by a local phone.

Comparison of Device-Cloud Signatures. Having answered the main question (*i.e.*, that there are indeed Device-Cloud signatures even when devices are triggered by IFTTT), a secondary question is whether the signature varies depending on the way the device is triggered. To answer this question, we consider the TP-Link plug, the D-Link plug, and the Rachio sprinkler, and we trigger events in three different ways:

- Local-Phone: signatures are extracted from the previous experiment (Table VII), using the vendor's official Android application to trigger events. The phone is connected to the smart home testbed network.
- 2) Remote-Phone: signatures are extracted from training datasets we collect using a remote phone setting (without using IFTTT). We use the vendor's official Android application to trigger events for each device. We connect the phone to a different network than the smart home testbed network.
- 3) IFTTT: signatures are extracted from a training dataset collected with the IFTTT home automation experiment described in this section.

Table IX lists all the Device-Cloud signatures we extract. We can see that the majority of Device-Cloud signatures are the same or very similar across the IFTTT, Local-Phone, and Remote-Phone experiments. For the TP-Link plug, the Device-Cloud signatures from the three experiments are the same or similar (same packet sequences within 1B). For the D-Link plug, the Local-Phone and the Remote-Phone Device-Cloud signatures are the same, but the IFTTT Device-Cloud signatures are partially similar to the Local-Phone and Remote-Phone Device-Cloud signatures. For the Rachio sprinkler, the Device-Cloud signatures from the three experiments are subsets of one another.

C. Traffic Shaping and Injection

Stochastic traffic padding (STP)¹² is a state-of-the-art defense for passive inference attack on smart home devices [10]. The shapes real network traffic generated by IoT events and injects fake event traffic randomly into upload and download traffic to imitate volume-based signatures. We contacted the authors of [10], but they did not share their STP implementation. Therefore, we simulated the VPN-based STP implementation, and performed a simple but conservative test. We used OpenVPN to replay packets from our prerecorded smart home device events. Alongside 100 real events, we injected 100 dummy STP events of the same type distributed evenly and randomly throughout the experiment. Our experiments with OpenVPN reveal that it consistently adds a header of 52 bytes for client-to-server packets and 49 bytes for server-to-client packets: thus our signatures remain intact. However, all traffic is now combined into one flow between two endpoints, and this could potentially increase the FPs.

In our STP experiments, PINGPONG performs well and STP has very little effect on our signatures: it does not generate many FPs: the average recall remains around 97% and the FPR increases to 1.09 per 100 dummy events of the same event type: the FPR increase is minimal. Table VII reports additional false positives for 3 devices: Arlo camera, Nest thermostat, and TP-Link light bulb. Further inspection revealed that these FPs were caused only by 2-packet signatures, while longer signatures were more resilient. The small increase occurs for two reasons: (1) the VPN tunnel combines all traffic into one flow, and (2) the dummy event packets are sometimes coincidentally sent from both endpoints simultaneously, allowing the request and reply packets to be in the same signature duration window (see Section V-G). Thus, a VPN-based STP implementation is not effective in defending against our PINGPONG; this is expected as STP was designed to defend against volumebased signatures, while our signatures consist of sequences of packet lengths, which survive both traffic shaping and injection. Furthermore, this defense is currently only applicable against the WAN sniffer adversary, while the Wi-Fi sniffer is not affected by this router-based implementations of STP.

¹⁰PINGPONG did not extract Device-Cloud signatures from 4 devices: the Sengled light bulb, Ecobee thermostat, SmartThings plug, and Kwikset lock. For the Ecobee thermostat, SmartThings plug, and Kwikset lock. PINGPONG extracted signatures from the Phone-Cloud communication (not from the Device-Cloud communication) in the previous experiment (see Table VII). For the Sengled light bulb, the device was recently forced to update its firmware—PINGPONG in its current state did not extract signatures in the Device-Cloud communication anymore although there is potentially a new signature.

¹¹We repeated our previous experiment and found that the Device-Cloud signatures presented in Table VII have evolved over time and since the original experiment.

¹²It is worth clarifying that despite its name, STP does not perform packet padding. It performs traffic shaping and injection (referred to as "traffic padding" in [10]) of fake traffic that resembles the real IoT traffic.

¹³Other examples of traffic injection include [36] that injects fake/spurious HTTP requests to defend against website fingerprinting.

Device	Model	Event	Signature	Duration (ms)
				Min./Avg./Max.
			Existing TP-Link Devices	
TP-Link plug	HS-110	ON	*S1: PH-172 D-115	406 / 743 / 10,667
			S2: C-592 S-1234 S-100	
		OFF	*S1: PH-172 D-115	
			S2: C-593 S-1235 S-100	
TP-Link light bulb	LB-130	ON	*S1: PH-258 D-288	8 / 77 / 148
_		OFF	*S1: PH-258 D-305	
		Intensity	S1: PH-[240-242] D-[287-289]	7 / 84 / 212
		Color	S1: S1: PH-317 D-287	6 / 89 / 174
		•	Newly Added TP-Link Devices	
TP-Link two-outlet plug	HS-107	ON	S1: PH-219 D-103	1,083 / 1593 / 2,207
1 0			S2: C-300 C-710 S-1412 S-88	
		OFF	S1: PH-219 D-103	
			S2: C-300 C-711 S-1413 S-88	
TP-Link power strip	HS-300	ON	S1: PH-219 D-103	976 / 1,537 / 4,974
•			S2: C-301 C-1412 S-[1405-1406] S-88	
		OFF	S1: PH-219 D-103	
			S2: C-301 C-1413 S-[1406-1407] S-88	
TP-Link white light bulb	KL-110	ON	S1: S-[414-415] C-[331-332]	1,892 / 2,021 / 2,157
			S2: C-648 S-[1279-1280] S-88	
		OFF	S1: S-[414-415] C-[350-351]	
			S2: C-649 S-[1280-1281] S-88	
		Intensity	S1: S-[479-483] C-[329-332]	2,418 / 2,540 / 3,610
			S2: C-[654-656] S-[1285-1288] S-88	
TP-Link camera	KC-100	ON	S1: PH-256 D-162 PH-624 D-256 PH-72 D-111 PH-608 D-371 PH-97	804 / 1,105 / 1,739
			S2: C-1288 S-[1161-1162] S-100	
		OFF	S1: PH-256 D-162 PH-624 D-256 PH-72 D-111 PH-614 D-371 PH-97	
			S2: C-1289 S-[1162-1163] S-100	

TABLE X. SIGNATURES EXTRACTED FROM DIFFERENT TP-LINK DEVICES, *THESE ARE THE LATEST SIGNATURES FOR THE TP-LINK PLUG AND TP-LINK LIGHT BULB (PER DECEMBER 2019).