Towards a Unified Trust Framework for Detecting IoT Device Attacks in Smart Homes

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***Abstract*—Trust in Smart Home (SH) Internet of Things (IoT) technologies is a primary concern for consumers, which is preventing the widespread adoption of smart home services. Additionally, the variety of IoT devices and cyber attacks make it hard to build a generic attack detection framework for smart home IoT devices. In this paper, we present a roadmap towards building a *unified* approach towards establishing trust scores as an indicator of the security status of an IoT device in a smart home that works across multiple attacks and device types/protocols. Specifically, we first introduce artificial reasoning inspired evidence collection approach by introducing a small set of factors that are affected significantly if a smart home IoT device is under attack. Thereafter, we propose an explainable trust scoring model that maps the device level evidence into trust scores in a way that produces lower trust scores when devices are under attack. Specifically, the trust model involves an Augmented Bayesian Belief based Model embedded with novel non-linear weighing functions; explicitly designed to account for the severity of the attack, probabilistic discounting of parts of the evidence caused by benign changes, thus explaining our success. For evaluation of the framework, we use two real datasets that contain a variety of actual cyber-attacks and benign traffic from seven different smart home IoT devices. Our evaluation seeks to investigate the generality of our framework across multiple datasets, with various classes of IoT devices and cyber attacks.**

***Index Terms*—Internet-of-Things, Trust, Security, Smart Home, Artificial Intelligence based Security, Machine Learning**

I. Introduction

Smart Homes are environments offering services to home inhabitants via a network of communication-enabled IoT devices that contain embedded software. IoT devices communicate with each other/remote service providers and often make decisions without human intervention. However, the concept of a smart home is a cornerstone of smart connected communities. Smart home exposes the most private and vulnerable of our personal spaces to the internet, which is known to be vulnerable to several classes of cyber-attacks [1].

Nonetheless, traditional cyber threats at best had economic impacts on businesses and breaches of personal data at rest. In contrast, in the evolving paradigm of smart home IoT, the cyber attacks have an immediate civilian impact that is riskier. Moreover, there are new IoT technology-specific security challenges that need to be handled explicitly.

Since IoT devices have constrained memory and computational resources, strong on-device security solutions are barely possible without significantly reducing their usability. Additionally, there is a lack of vendor motivation to implement security schemes in IoT products [2] due to cost versus utility trade-offs, while other vendors do not implement too much security to improve latency and quality of service and reduce costs [3]. For example, after analysis of smart home data, researchers in [2], [3] found only one IoT device that uses secure encrypted SMTP protocol, and only 'some' IoT devices use secure HTTP port (HTTPS 443), and most other IoT devices are using insecure HTTP over port 80. We did not find any device use the MQTT secure port 8883 [4]. There is a lack of standards in IoT protocols and port mappings that makes it hard to have an established rule or specification based attack detection that is common to all IoT devices.

A. Challenges and Motivation

Prior work on IoT device attacks can be broadly classified into the following categories network-level data flow [5] , device-specific fingerprinting [6], attack specific [7], network segmentation [8], localization approaches [9], IoT network or device components classification [11], embedded security architecture [12], or adopt known machine learning techniques for anomaly detection [10]. Localization based approaches only take care of physical proximity issue that is more related to authentication but does not detect attacks on already authenticated devices. Similarly, network segmentation involves splitting the smart home network channel to various sub-networks to mitigate the movement of attacks, but do not detect them actively. Device-specific approaches do not scale due to the large heterogeneity of device types that can be found in smart home IoT markets. Similarly, attack specific approaches need separate solutions for each cyber attack. Therefore, the number of solutions for providing a secure smart home increases.

Therefore, there is a need for a more unified solution that is not attack or device-specific, but that which generalizes across most attack types, devices, and services in smart home IoT.

B. Contributions of this Work

In this paper, we propose a 'unified' approach towards establishing trust scores as a reliable indicator of the security status of IoT devices in a smart home. Our framework contains

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a series of modules: (a) service level access rules, (b) evidence collection via proposed unified factors, (c) trust scoring module. Specifically, our service access rule mechanism takes a service-level view, establishing baseline access rules of authorized communication flows from IoT applications. Thereafter, our evidence collection module proposes a unified set of novel factors that are affected significantly if a smart home IoT device is under attack while provisioning for benign changes in network behavior. Such a body of evidence, carefully collected over time, serve as inputs to the trust scoring module. Finally, the trust scoring module maps the device-specific evidence (observations) into trust scores, such that it produces lower trust scores when devices are under attack. Specifically, we propose a Bayesian Belief based Model augmented with novel non-linear weighing and activation functions, designed specifically for our problem. The weighing functions contain embeddings of certain explainable factors and are designed such that the severity of the attack, probabilistic discounting of parts of the evidence caused by benign changes are appropriately embedded in the scoring module; that explains our success under attacks while preventing false alarms.

For the evaluation of our framework, we use two different datasets containing various actual cyber attacks and benign behaviors for various IoT device types. Our evaluation seeks to investigate the generality of our framework across multiple datasets, devices, and attacks, compared to existing solutions that treat each of these aspects in silos. The remaining paper is organized as follows: Section II system model, Section III threat model, Section IV proposed framework, Section V, experimental results, and conclusion.

II. Smart Home IoT System Model

This section introduces several pieces of network components that help us understand the smart home network architecture, as shown Fig. 1. Such components include (1) IoT devices (low computation devices), (2) non-IoT (high computation) devices, (3) IoT hub devices, (4) smart home gateway (edge/fog node), and the (5) cloud gateway (cloud node).

A. Device Types

A smart home (SH) contains various types of IP enabled devices. It is important to differentiate between IoT devices and non-IoT devices, as shown in Fig. 1. Based on the computational ability, an SH can have low computation power (IoT) and high computation power (non-IoT) IP devices.

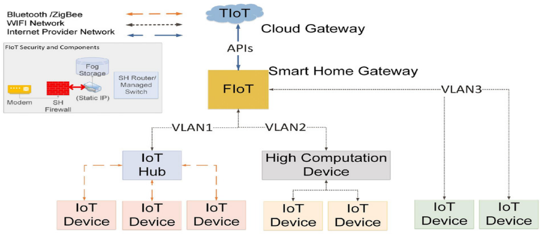


Figure 1: Smart Home Network Architecture

Low computation IP Devices (IoT): An IoT device is an IP-enabled device (e.g., smart camera) that has limited computational abilities compared to laptops/smartphones/tablets, and offers a small set of services to the smart home (SH) owner (e.g., smart surveillance). Each IoT device has an API (or simply app.), that enables it to offer corresponding SH services. The service is offered to the SH owner when an IoT device's corresponding app. connects to specific servers (on the rest of the internet/within the LAN) on which IoT service providers host their services. Thus, there is a mapping between an IoT device apps and services.

High computation IP devices (non-IoT): These are devices that may host apps/APIs that allow the use of IoT services offered by IoT devices. Examples of such high computation IP devices include smartphones, tablets, laptops. These devices typically install many apps and software on their OS. All other sensors and actuators that are not enabled by an IP address, but collect data and perform actions, are not considered as IoT devices. The security of such devices is beyond our scope.

Smart Home Gateway (SHG) and FIoT: Each smart home has a gateway router (SHG), that connects the IoT devices to the rest of the internet. This SHG supports services such as Network Address Translation (NAT), Software Defined Networking (SDN), and can also host middleware services using a Raspberry-Pi micro-controller. Our proposed trust model is deployed on the smart home gateway router (SHG) as a FIoT middleware. All smart home services are managed and controlled by the edge/Fog Internet of Things Middleware (FIoT) that is within the home network. Thus, FIoT will be able to monitor SH network activity originating from a given smart home.

B. Smart Home Operations

Let each IoT device be denoted by $i \in \{1, 2, .., I\}$, where I is the total number of IoT devices in the smart home. Each such IoT device, *provides a set of services* with the help of *one (or more) apps*. The set of services is represented by the set $S^{(i)} \in \{1, \cdots, k, \cdots, K^{(i)}\}$, and the set of apps is represented by $A^{(i)} \in \{1, \cdots, j, \cdots, N_j^{(i)}\}$, where k and j denote any given service and an app respectively, while $K^{(i)}$ and $N_j^{(i)}$ are total number of services and apps offered by the i-th IoT device, respectively. In most cases, IoT devices have a single app that provides multiple services, but occasionally it might contain multiple apps. Therefore, the set of services offered by a home is $\bigcup_{i=1}^{I} S^{(i)}$.

Scope of Our work: We make the following assumptions for our work: 1). The use of a cellular network for any communication directly from IoT devices is beyond the scope of our work. We only consider the smart home network, which communicates through the WiFi or wired LAN that is managed and controlled by the FIoT middleware hosted on SH Gateway. This paper only intends to detect misbehavior by smart home IoT device applications connect via a smart home

WiFi network that uses a central gateway router. 2) Our scope does not include the detection of the data leakage caused by the non-IoT devices/applications of the smart homeowner.

III. Threat Model

We characterize the threat model by various attack types, strengths, and strategies:

Direct Attacks: In the direct attack in SH, the attacker flood victim that could be within/outside the SH network from a compromised IoT device. The direct attack types included in our labeled attack dataset include well-known attacks such as Fraggle, Ping flood, and TCP SYN [10], [15].

Reflection Attacks: the SH reflection attack, the attacker uses a spoofed IP (SH IoT device IP) for attacking victims; in this way, the attacker uses SH IoT devise as a weapon for targeting the victim. Types of Reflection attacks include:

(i) *Custom Malware Campaigns:* These are malicious campaigns, where software designed to disrupt IoT device operations, usually used to create a Distributed Denial of Service (DDoS) attack. In many instances, such malwares are known to show movement and grow their attacks from one to more SH IoT devices and services, taking down a large section of important network entities. In this work, our experiments contain data from the malwares Hide and Seek, Muhstik, Torii, the most advanced botnet malware, according to Avast security researcher, that can attack many device architectures.

(ii) *SMURF:* it is a network attack where the attacker floods the SH router with spoofed ICMP traffic via sending a request to IoT devices with a spoofed source IP of the victim server. Thus, the device will reply to the targeted victim IP. The attacker's goal is to disturb the victim's server operations. Such attack behavior is to use the SH IoT device as a weapon for targeting victim servers and is relates to the number of packets being sent per time interval.

(iii) *SSDP reflection:* it is a malware app running on smart home IoT devices by using the Simple Service Discovery Protocol (SSDP) used to discover IoT devices in SH. It also uses Universal Plug-n-Play (UPnP) port forwarding to allow a direct attack on IoT devices by an external attacker [15]. Mainly, the SSDP and UPnP port forwarding are conventional in SH network because some IoT devices support peer to peer applications. The adversary uses the SSDP protocol to discover the devices and services in SH without explicit configuration using SSDP vulnerabilities.

(iv) *SNMP reflection:* During an SNMP reflection attack, the adversary sends out a large number of SNMP queries with a spoofed IP address (of victim's IP) to smart home IoT devices, that in turn reply to that victim IP instead of the attacker IP. The attack volume grows as the number of compromised smart home IoT devices (that continue to reply to the victim) increases, the victim becomes crippled, due to the huge volume of SNMP responses.

Co-Domain DDoS and Leakage: This kind of attack takes advantage of the IP/port forwarding feature that is argued as necessary to support QoS guarantees by ensuring server availability and load balancing. Therefore, a designated server may forward IoT device requests to other servers in the same network/cloud domain or third party providers. In such an instance, the IoT device gets a response/requests from a different server other than the typical server of the IoT provider. Normally, such occurrences are less during benign conditions; however, increased frequency and volume of such events should indicate suspicion. This is because many servers belonging to the business rivals/competitors/adversaries may be co-located in the same network/cloud domain as the designated server for that service. Taking a completely conservative approach of treating every such instance as suspicious will either increase false alarms, reducing the efficiency of IoT services.

Attack Strength Variation: IoT devices have a limited processing capability for network traffic. Therefore, if the reflection attack is too high in volume, the device may stop working altogether. Intelligent attacks would like to keep compromised devices still operational to allow launching attacks on other machines. In such cases, the attacker may keep traffic rates low because it wants to conceal the attack's effect or if its real target is not the IoT service provider.

In another attack, the attacker may be willing to make the IoT device less or not functional, and thus keeps traffic rate medium or high accordingly. Thus, traffic volumes, even for the same attack type, vary according to the goals or motivations of adversaries who are difficult to predict. To embed this, we parameterize the attack volume by varying attack strengths in our simulated dataset. From the real dataset obtained from [10], [19], we used three different attack strengths per attack: (i) high attack traffic rate, which generates 100 packets per second (pps), (ii) medium attack traffic rate, generate 10 pps, (iii) low attack traffic rate that generates 1 pps.

IV. Proposed Framework

Our proposed framework will be deployed as a framework in the FIoT, which inspects and manages data plane traffic flow (e. g., recording source and destination IPs:port mappings) to/from all SH IoT devices. Our framework has three main phases: (a) Access Control Policy Engine (b) Evidence Collection via Unified Factors, (c) Trust Scoring Model.

The Access Control Policy engine sets baseline rules of benign access for the apps of each IoT device. Thereafter, based on which parts of traffic flow attributes align with the service level access control policy, we propose a set of unified factors that remain largely unaffected under legitimate benign changes but show variations under attacks. These sets of factors produce a set of features per device as a body of evidence that serves as an input to our proposed trust scoring model. This evidence collection phase partly uses the ACL to compare network traffic attributes captured at the FIoT, although there are non-ACL aspects of evidence collection. Our trust scoring model is an artificial intelligence inspired approach that maps evidence into trust scores, such that devices under attacks show lower scores compared to when they are not attacked.

A. *Service Access Rule Policy*

Typically, an access control policy engine sets static and dynamic access rules (known as Access Control List (ACL)) for devices explicitly registered with the FIoT. The decision on whether a device should have authorized access to a service is contextually related to the functionality.

While IoT devices exhibit heterogeneity, the number of services they offer is limited. The Manufacturer Usage Description (MUD) is a novel IETF specification that offers suggestions on the expected behavior of an IoT device contextually related to the services it offers. Specifically, the key idea of the MUD is to return a list of acceptable or expected destination DNS names and destination port numbers, which identifies one or more designated servers for the corresponding service that an IoT device should offer as well as ancillary end-points it might communicate to. Although not a security specification itself, MUD profiles can be used as a first step towards protection.

Note that what is included in the MUD specification, and how security engineers/administrators interpret the MUD specification for access control are deciding aspects for achievable security level. In a previous work [10], the idea of the access control list was synonymous with the MUD profile. Their idea of the MUD profile was to include all communication patterns observed in the benign dataset. However, our treatment of access rules is different from previous work, since *we differentiate between MUD and access compliance*.

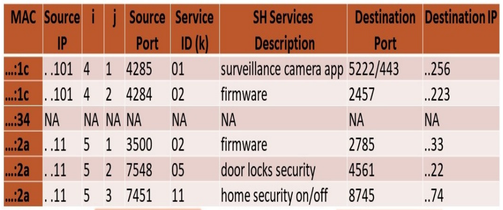
Our FIoT uses the DNS lookup to resolve the domain name in the MUD to the IP address of the servers that are supposed to offer the services. Thus, MUD can be used to point all IPs and port no.s. that should be offering services or communicating with that IoT device. Now, this most commonly includes the IoT service provider and the hardware vendor. For specific IoT devices like smart cameras and home assistants, they connect to a lot of different servers other than the service provider, and there the volume of packets exchanged is important. Hence, our ACL design goal is to manage a table that sets baseline benign access rules of each IoT device i's app/firmware j both the client-side (Source devices) and server (Destination) side based on the above awareness.

1) **Client Side:** When an IoT device is first introduced in SH, it has to be registered with the FIoT as an authenticated device. The *Source IP, Source MAC, and Source Port Number* is first added to the ACL. In this way, FIoT makes sure that all active data flows at-least do not directly come from outside the network and are registered IoT devices based on their IP and MAC addresses.

2) **Service Side:** To find a mapping between IoT devices and their corresponding designated server's (that provide its service) destination port numbers, destination IPs, and DNS names, our FIoT queries the MUD server that returns a port-based list that specifies those DNS names, and ports and that should be typically accessed by a given service offered by an IoT device. The MUD URLs are updated via various IoT providers and manufacturers. While not all manufacturers subscribe to the MUD specification, it is becoming common over time, and thus will become a practical approach. The information added to the ACL includes *Destination Port No., Destination IP, Service ID, Service Type*, as shown in Fig. 2. Note that we only put the designated IoT service provider server as a whitelist entry. Everything else is subject to different levels of suspicion as detailed in the factors for evidence collection. The reason for doing this is given below:

From studies of datasets, we found gray areas in IoT devices such smart cameras (that use STUN protocol) or IoT home assistants, which need to access random unauthenticated servers that may or may not be servers in the same cloud domain, as the IoT provider. Making them part of ACL may cause missed detection of attacks. Additionally, we have found several cases where IP and port forwarding causes the response to arrive from a different server than the one listed on the MUD profile. Thus, using the MUD directly as ACL will increase false alarms. Additionally, packets are exchanged for maintenance or monitoring purposes between the hardware manufacturer and device, but such an occurrence is 'infrequent'.

Our view of a service based ACL includes the following: Each IoT device has a list of authorized IPs (corresponding to servers that provide services related to that IoT device) for each app(s) hosted by that device. For example, the services of IoT device i is provided by using two apps j_1 and j_2 services app, where both j_1 and j_2 allowed to have a conversation with only specific devices and servers using IPs of these devices as presented in Fig 2. The app/firmware is present in the form of destination IP:port entry.



MAC	Source IP	i	j	Source Port	Service ID (k)	SH Services Description	Destination Port	Destination IP
....:1c	. .101	4	1	4285	01	surveillance camera app	5222/443	..256
....:1c	. .101	4	2	4284	02	firmware	2457	..223
....:34	NA	NA	NA	NA	NA	NA	NA	NA
....:2a	. .11	5	1	3500	02	firmware	2785	..33
....:2a	. .11	5	2	7548	05	door locks security	4561	..22
....:2a	. .11	5	3	7451	11	home security on/off	8745	..74

Figure 2: Smart Home access control policy

B. *Evidence Collection Mechanism*

A communication (packet exchange) not matching the ACL does not automatically mean an attack and requires further checks that we incorporate in our evidential model. Typically, anything that does not match with an ACL is denied or deemed suspicious, thus increasing false alarm rates, decreasing usability. Our interpretation of service level access control is not strictly binary due to the observed variations in IoT behaviors. Similarly, interaction confirming the access control list does not necessarily imply no attacks, which we also incorporate in our evidential model. The above awareness is central to our design of *unified set of factors*. From here, we will refer to the packet exchange via the FIoT as an *interaction*.

Intuitively, the body of evidence should point towards degrees of positive, negative, possibly suspicious interactions based on the body of evidence. The goal is to find (i) a methodology for labeling the interactions; (ii) corresponding mathematical representations of these factors (known as features) that captures the effects of attacks in a numerically quantifiable way. Thus, features form the mathematically tractable evidence that is driven by our proposed set of factors.

We propose the following set of factors: (1) Service Access Uncertainty (2) Cumulative Volume of Uncertain Accesses (3) Service Access Violation (4) Access Violation Diversity. Below we describe each of these factors.

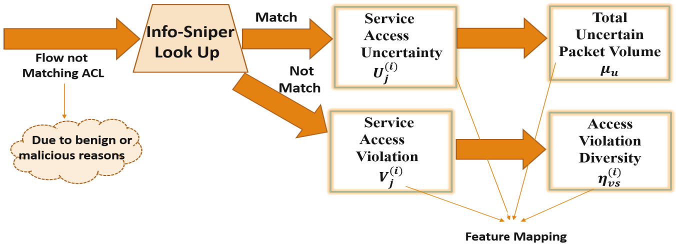

Info-Sniper Look Up
Flow not Matching ACL
Match
Not Match
Due to benign or malicious reasons
Service Access Uncertainty $U_j^{(i)}$
Total Uncertain Packet Volume μ_u
Service Access Violation $V_j^{(i)}$
Access Violation Diversity $\eta_{vs}^{(i)}$
Feature Mapping

Figure 3: Evidence Collection

1) **Service Access Uncertainty:** Packet flows originating from a device not matching the destination IP and Ports in the ACL may or may not be necessarily due to an attack. Hence, an intelligent framework should not blindly label this event as a negative interaction. Not matching flows can be attributed to *benign 'events'* in smart home IoT operations, such as:

(1) Hardware Vendor checks: Packets are sent from IoT devices to servers that belong to their third-party vendors for monitoring purposes (such as estimating the remaining life of a device, etc.). (2) IP and port Forwarding: Sometimes, traffic is redirected to a different IP or Port than the designated one in the MUD, to guarantee quality of services (QoS) issues (e.g., too many requests concurrently can be forwarded) or in case of server maintenance/upgrades/downtimes. In such cases, the incoming response to an IoT device comes from a different server but is usually within the same network/cloud domain as the authorized server in the ACL. (3) use of STUN servers for smart cameras and video streaming services: From our study of smart home IoT datasets and previous literature, we found most cameras use the UDP port 3478 for communicating with various servers on a peer to peer mode to allow seamless access to smart surveillance from anywhere. Such servers cannot be learned and included from the MUD profile.

However, the above, if treated as a match in the ACL can allow adversaries to create cyber attacks on servers within the same cloud domain, third party vendors, or those that host streaming. This gives the intuition that we should treat them as between a match and mismatch(i.e., uncertain). Therefore, we believe that once a packet exchange does not match the baseline ACL, we first check if it might be due to any of the above three reasons by the following procedure (summarized in Fig. 3).

Our FIoT queries an IP lookup service *Info-Sniper* [24], that provides meta information for any IP recorded in the network traffic. This information includes: (i) Name of the Owner/Provider (ii) Geolocation (iii) DNS name (iv) Time Zone. Therefore, packets sent to a given destination IP is checked by our FIoT to ascertain whether the Name of the Owner and other attributes match with (1) any of the third party vendor/manufacturer of the IoT device, (2) whether they are within the same cloud/network domain name, or (3) use the STUN protocol's UDP port (if the device offers streaming video services). To conclude, if a packet exchange does not match the access control list, the FIoT checks for the above-mentioned possibilities using the context information queried from the Info-Sniper lookup service. If there is a match, we label this packet flow as 'uncertain.' If not, then we would label this packet exchange as a violation. Mathematically, we denote an uncertain packet exchange for services as $U^{(i)}(s)$.

Number of Uncertain Packets Per Time Window: Therefore, the corresponding feature that we keep track is the total number of uncertain packet exchanges for a given device i within a time window T, denoted as

$$\eta_u^{(i)}(T) = \sum_T U^{(i)}(s) \tag{1}$$

2) **Cumulative Volume of Uncertain Accesses:** One important fact about the events that cause uncertainty is that when they are due to benign behavior, the packet volume is low. Uncertain exchanges can be allowed a benefit of the doubt (discounted) while calculating the trust scores of a device. However, beyond a certain volume of total uncertain exchanges, this situation should be viewed as suspicious, owing to the infrequent pattern of such occurrences. This aspect is later embedded using an uncertainty weight function, which is a function of the total uncertain packet volume.

Cumulative Sum of Uncertain in a Time frame: At each time window, we keep a cumulative sum of uncertain interactions over a sliding frame of previous F time windows.

$$\mu_u(T) = \sum_{T-F}^{T} \eta_u^{(i)}(T) \tag{2}$$

3) **Service Access Violation:** The next factor for evidence collection for potential malicious activity is the service access violation. The main idea is that if an interaction from an IoT device does not match the authorized access control list entries and can neither be reasoned as uncertain, then this event of access is treated as a violation represented as $(V_j^{(i)})$, i.e., the violation of app j that runs inside the device i.

Number of Violation Packets Per Time Window: In fact, for that time window, T, the FIoT middleware calculates the total number of access violation of K services by all the apps j_1 to j_n running on IoT device $(V_j^{(i)})$.

$$\eta_v^{(i)}(T) = \sum_T V_j^{(i)} \tag{3}$$

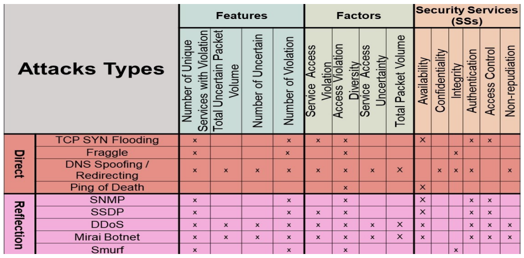
4) **Access Violation Diversity:** The Access Violation Diversity w_d represents the extent of the cross-section of services/servers being affected by a set of violations. Suppose if one device is trying only to access one service ten times, whereas another device is trying to access ten different unauthorized services, within the same time window T, the second scenario is far more serious from a security perspective. Thus, Access Violation Diversity is an important feature to determine how the attacker is trying to grow its attack impact and compromise more resources.

Number of Unique Services with violations $\eta_{vs}^{(i)}(T)$: The number of unique services that experienced violations recorded for a given IoT device i in a time window T. Mathematically, it is represented by the following:

$$\eta_{vs}^{(i)}(T) = \sum_{s=1}^{K} I(i,s) \tag{4}$$

$$\text{where,} \quad I(i,s) = \begin{cases} 1, & \text{If } i \text{ violated service } s \\ 0, & \text{Otherwise} \end{cases} \tag{5}$$

From the network traffic analysis of attacks (in a cross-validation set), we found common links between different attacks. Once our rule of matches, violation, and uncertainty are in place, most real IoT cyberattacks either registers violation with increased packet volumes, or an abnormal increase in the cumulative volume of packet exchange to uncertain destinations, as well as the relative volume of uncertain interactions. In Fig 4, we show a summary of the observed relationship between different types of reflection and direct attacks, and the factors we put forward, which succinctly explains why our factors work in terms of building the appropriate evidence.



Attacks Types		Features				Factors				Security Services (SSs)					
		Number of Unique Services with Violation	Total Uncertain Packet Volume	Number of Uncertain	Number of Violation	Service Access Violation	Access Violation Diversity	Service Access Uncertainty	Total Packet Volume	Availability	Confidentiality	Integrity	Authentication	Access Control	Non-repudiation
Direct	TCP SYN Flooding	×			×	×	×			×			×	×	
	Fraggle	×			×		×					×			
	DNS Spoofing / Redirecting	×	×	×	×	×	×	×	×		×	×	×		×
	Ping of Death						×			×					
Reflection	SNMP	×			×		×			×			×	×	
	SSDP	×			×	×	×			×			×	×	
	DDoS	×	×	×	×	×	×	×	×	×			×	×	×
	Mirai Botnet	×	×	×	×	×	×	×	×	×			×	×	×
	Smurf	×			×		×					×			

Figure 4: Attack and Factor Mapping

C. Trust Scoring Model

Note that comparison of packet exchanges with ACL has only three mutually exclusive outcomes, viz., matching, violation, and uncertain interaction. Notice that access violation diversity and volume of uncertainty are not mutually exclusive to violations and uncertain, so we ignore them for now. Based on the evidence and the past evidence (if available), it is well known that the posterior probability of observing a matching, violation, or an uncertain interaction can be calculated using posterior beliefs calculated using Bayesian inference where the data is a multinomial distribution of the number of matches, mismatches, and uncertainty.

Previous studies [20] have shown that for multinomially distributed data D_i with a non-informative prior, the posterior probability belief θ_i is given by the mean of Dirichlet distribution as the following:

$$f(\theta_i|D_i) = \frac{D_i + 1}{\sum_{i=1}^{K} D_i + K} \tag{6}$$

Where K is the total number of mutually exclusive categories in the evidence state space, i is the i-th category, and D_i is the frequency of occurrences of the i-th event in the data.

Degrees of Disbelief and Uncertainty Using the result in Eqn. 6, we apply the known derivation provided in [21], to find the degrees of disbelief and uncertainty as:

$$d^{(i)} = \frac{n_v^{(i)} + 1}{N^{(i)} + 3} \qquad u^{(i)} = \frac{n_u^{(i)} + 1}{N^{(i)} + 3} \tag{7}$$

Embedding Access Violation Diversity: However, in Eqn. 7, the $d^{(i)}$ only indicates the proportion of violations to the total number of accesses. It does not provide any idea on the attack scale or surface over which this proportion of violation was recorded. If the same proportion of violation is recorded from a unique number of devices, this is a more severe attack than the same proportion of violation targeting only one device. Therefore, we need to add weight to the $d^{(i)}$, which embeds the importance of how many unique devices were involved in the observed proportion of violations. This is similar to neural learning approach. The question is what functional form should describe this behavior. We use a modified softplus function scaled between zero and one, by the following Eqn.

$$\tau_v^{(i)} = log(ae^{\eta_{vs}} + 1) \tag{8}$$

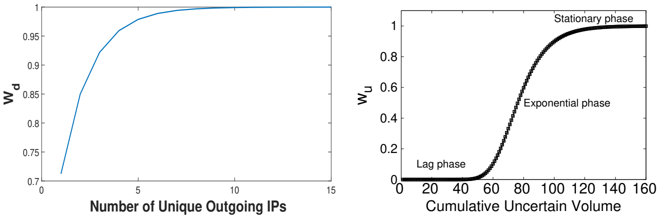
where $0 < \tau_v < \infty$. The above Eqn. is a modified softplus function, with an augmented parameter a, which controls both the steepness of the function and the initial bias (y-intercept) of τ_v when $\eta_{vs} = 0$. Finally, we scale this to an interval between 0 and 1, giving the final equation for the weight of the violation.

$$w_d = 1 - e^{-|\tau_v|} \tag{9}$$

Thus the combined disbelief mass $w_d.d^{(i)}$. The product indicates heightened suspicion that cyber attack is more serious, if the surface is larger.

Embedding Cumulative Uncertain Volume: The intuition behind the design of the weighing function of the raw, uncertain probability mass is that the suspicion increases as more number of uncertain interactions emerge. However, up to a certain number of uncertain interactions should be discounted.

$$w_u = \frac{1}{(1 + A_b.e^{-B_b \mu_u})^{1/\nu}} \tag{10}$$



(a) Disbelief Weight (b) Uncertainty Weight

Figure 5: Functional Forms of w_d and w_u

where $A_b > 0$ is the initial bias, $0 < B_b < 1$ is the growth rate parameter, $0 < \nu < 1$ is the displacement parameter. The lag phase in w_u discounts the effect of the u, if the total cumulative volume in the current frame is low indicating a benign scenario. The parameter selection process is discussed later.

Expected Belief Score We envision trust score is a 'complement of total disbelief,' which includes the weighted violation and weighted uncertainty masses that should contribute to disbelief. This is mathematically represented as the following:

$$TR^{(i)} = 1 - w_d.d - w_u.u \tag{11}$$

Plugging in w_d, d, w_u, u into Eqn. 11, we get TR^i. Now we know that in logistic regression, the response variable is linked to the independent variable via a non-gaussian distribution and therefore needs a link function. The typical link function for a binary response variable (trusted or not trusted). Typically, when the response is a binary, the following logit link function is an appropriate link function that is given by:

$$E^{(i)} = log\left(\frac{TR^{(i)}}{1 - TR^{(i)}}\right) \tag{12}$$

The Eqn. 12, facilitates trust scores that are linearly separable by a threshold that helps in classification between trusted or non-trusted devices. The $TR^{(i)}$ is in the interval between $+\infty$ and $-\infty$ that is scaled to the final trust score using 13.

The final trust score FR^i is scaled from the real value plane to an interval between [-1,+1] by the following equation, to maintain convention of trust metrics representation:

$$FR^{(i)} = \begin{cases} +\left(1 - e^{-|E^i|}\right), & \text{if } E^{(i)} > 0 \\ -\left(1 - e^{-|E^i|}\right), & \text{if } E^{(i)} < 0 \\ 0, & \text{if } E^{(i)} = 0 \end{cases} \tag{13}$$

The supervised approach is feasible if there is the availability of labeled datasets of attacks and no attacks. In such cases, the training set and cross-validation sets can be used to observe the difference in trust scores of the two classes. The cross-validation set includes a set of attack samples as well.

D. Parameter Learning

For optimal parameter selection of the trust model, one needs to decide on an appropriate loss/error function. In this case, our loss function e is the square difference of the sum of compromised device trust scores and the sum trust scores of honest device set, which will improve the classification. The goal is to *maximize* the e which defined as:

$$e = \left(\frac{\sum_{benign} FR^{(i)}}{H} - \frac{\sum_{attack} FR^{(i)}}{M}\right)^2 \tag{14}$$

$$\text{s.t.} \qquad A_b > 0; \qquad 0 < B_b < 1; \qquad 0 < \nu < 1; \qquad a > 0$$

where H and M are numbers of devices used in the cross-validation process from the benign and attack sets, in our case, H and M are equal since we have for each device an instance of the benign in the training and instance of the attack in the cross-validation set. The solution of Eqn. 14, can be done through two alternatives: (a) Grid Search Approach (b) A Gradient Descent based Approach. A gradient descent approach is more computationally efficient for finding the optimal parameters when the number of parameters is large, and the search space in each parameter is huge.

However, for the gradient descent approach to be applicable, the error/loss function needs to be convex, which is difficult to guarantee. In our problem, the number of parameters is less (i.e., 4), and two out of them have a limited search space. Hence, for simplicity, we use a brute force grid search method to find the parameter values that maximize the error function. Thus, we get an approximate optimal parameter selection.

Our definition can be easily extended to gradient descent by taking a negative logarithm of the above error function (which is concave). However, the resulting approximate convex function may need further processing to ensure the differentiability and existence of global minima. For this work, we have ignored the gradient descent based approach because the scale of our optimization problem has been made drastically smaller than the traditional ML techniques (via the set of unified factors), which have a large parameter set.

After the optimal parameters have been identified, we map the trust scores for a device for the benign and a small portion of the attacked dataset (cross-validation set). We then use an SVM to find the optimal separation between these labels of trust scores for all devices belonging to the UNSW dataset. The learned threshold Γ serves as a classifier in the test set.

V. Experimental Results

Here we present the experimental results of our scoring model. First, we provide a dataset description followed by the trust scoring observations for each device.

A. Dataset Description

For validating our model, we use devices from two different datasets: (1) UNSW Smart Home IoT dataset [10] and the (2) CTU Apostemat IoT-23 dataset [22].

The UNSW dataset contains a set of IoT and non-IoT devices and also MUD profiles. We select benign data of 10 days and attacked data of 5 days from four IoT devices (Amazon Echo, Phillips Hue Bulb, iHome Smart Plug, Samsung Camera) for showing performance. Our device selection is based on the attacked devices mentioned in previous work on [10] to compare performance. The attack dataset had contained: (i) direct attack (viz., TCP SYN (referred to as TCP SYN (D) in the table), and Fraggle) (ii) reflection attack (viz., SNMP, SSDP, DDoS, TCP SYN (referred as TCP SYN (R) in the table) Samsung Smart Camera, and iHome Plug. Out of the five days, two days were used as a cross-validation set, and the rest of the three days was our testing set.

We also used labeled benign and attacked database for real network traffic obtained from CTU Avast [22]. We used the second dataset to prove the generality of our framework. We chose two devices Somfy Smart Door Lock and Amazon Echo, that contain reflective DDoS attacks through malwares; *Torri*, *Hide and Seek*, and *Muhstik*. In Table I we present a mapping showing the implemented attacks launched against IoT devices in the labs of both UNSW and CTU datasets.

Table I: Mapping IoT devices with attacks

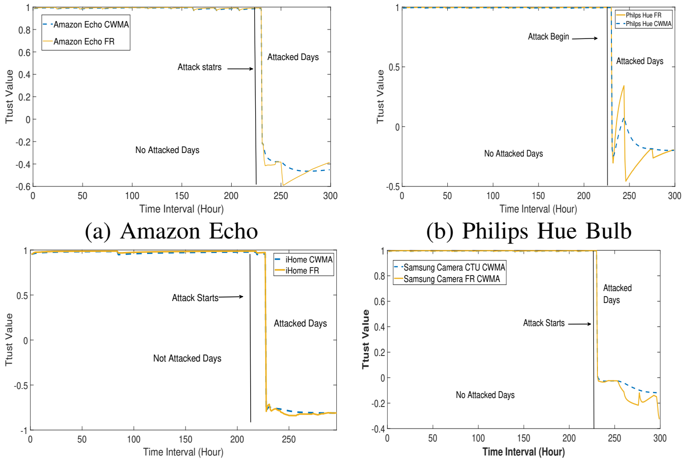
Attack types	Echo UNSW	Hue UNSW	S.Camera UNSW	iHome UNSW	Somfy CTU	Echo CTU	Hue CTU
Hide& Seek						X	
Muhstik							X
Torri					X		
SNMP			X				
SSDP		X					
TCP SYN (R)		X	X				
Smurf		X	X				
TCP SYN (D)		X	X				
Fraggle	X		X				
DDoS	X	X	X	X			

B. Experimental Set Up

We use Wireshark to parse the raw .pcap traffic files into CSV files and partition them to 10, 2, and 3 days of training, cross-validation, and testing sets. We create the ACL table flow rules based on MUD profiles. In this paper, we calculate all factors and features based on packets per second that we derive from the data as well as the flow directions. More details on this can be found [10]. However, how we interpret the MUD for the ACL and factor mapping is done differently than [10], as explained earlier, which explains better accuracy in our method.

In all the figures, we show a continuous evolution of trust by retrofitting the parameters across the whole duration of the dataset, to give a sense of how the real-time evolution of trust values happen as soon as there is some incidence of attack.

C. UNSW Dataset Results



(a) Amazon Echo

(b) Philips Hue Bulb

(c) iHome Smart Plug

(d) Samsung Smart Camera

Figure 6: UNSW Dataset: Trust Values over Time

Figs. 6a, 6b, 6c, 6d respectively correspond to results from the UNSW dataset, that shows the evolution of trust values for Amazon Echo, Phillips Hue Bulb, iHome Smart Plug, Samsung Smart Camera IoT devices. In each of these figures, both the instantaneous raw trust values per time window $FR^{(i)}(T)$ (dotted blue lines) and the cumulative weighted moving average over the instantaneous trust values(solid orange lines) are shown.

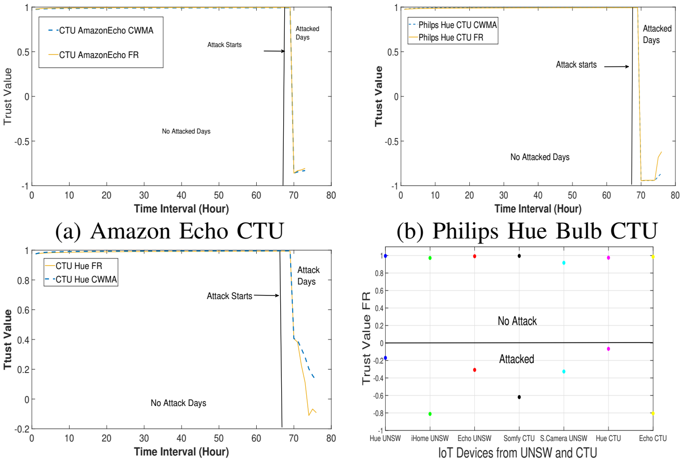
Additionally, each result has two regions; no attack days and attack days. Our three days of the testing set corresponds to the attacked days. To give a sense of how quickly our framework responds to the incidence of attacks, we created an augmented dataset with the ten days of benign set appended just before the three days of the test set (containing attacks). We then applied our model with the learned parameter. Below we describe the specifics of observations for each device in the UNSW dataset.

1) Amazon Echo: Amazon Echo device from UNSW contains Fraggle and ARP spoof attacks, as reported by [10]. Fig. 6a, shows that our framework produces reduced trust values in the attacked dataset compared to the benign dataset, prove that the FR value reflects the attack behavior.

2) UNSW Philips Hue Bulb: The Phillips Hue Bulb IoT device from UNSW contains attacks such as SSDP and SNMP reflection, Smurf, TCP SYN flood as reported by [10]. Fig. 6b, shows that trust values drop after the attacked dataset starts performing malicious activity. Here the attack volume is targeted to those within the cloud domain of the provider, and the attack volume is lower. Therefore the drop in the trust value is not as strong as in Amazon Echo. The start and stop times of each attack type are not labeled in the dataset, which proves that our method need not know such attack specifics for detection.

3) UNSW iHome Smart Plug: The iHome Smart Plug IoT device from UNSW, contain a DDoS attack launched after an ARP poisoning exploit [10]. Fig. 6c clearly shows the reduction in the trust value during the attack days, although the time it takes to start decreasing is much higher than the other devices. This is because the attack volume is at times lower than the benign total volume, as revealed from the data traces.

4) UNSW Samsung Smart Camera: The Samsung Smart Camera IoT device from UNSW contains attacks such as TCP SYN, Fraggle, SMURF etc. and reported by [10]. Congruent to previous observations Fig. 6d, the progression of decrease



(a) Amazon Echo CTU

(b) Philips Hue Bulb CTU

(c) Somfy Smart Door Lock

(d) Steady State Trust Values

Figure 7: CTU Dataset: trust values over time

in trust values is rapid after the attack days start showing that our method can detect the attack behavior.

D. Proving Performance Generality over CTU dataset

The CTU dataset contains 69 hours of benign data for all devices and 4 to 7 hours of attacked data depending on the device type. The attacks belonged to custom malware campaigns such as Hide Seek, Torri, and Muhstik, and the device mapping with the malware are shown in Table I. Here there is no cross-validation; we apply our model and parameters from the UNSW dataset to evaluate the generality of the method.

1) Time Evolving Trust Values: Fig. 7a, shows the drop in trust values for an amazon echo device from the CTU dataset with a Hide and Seek attack, within an hour of the start of an attack. The Fig. 7b shows similar observations for a Phillips Hue bulb containing Muhstik malware attack.

Fig. 7c, shows a new IoT device type not found in the UNSW dataset. However, our model still detects attacks on this device, which did not feature in either the training or parameter selection process. We can observe from Fig. 7c that regardless of this, our framework is still able to detect this attack, although the time to detection is larger compared to the other devices.

2) Steady State Trust Values: The Fig. 7d, shows a steady-state trust value difference between the no attacked days and attacked days that compares different device final trust value at the end of the benign and the attacked test set and how far it is from the threshold $\Gamma = 0.02$ obtained by SVM over the cross-validation set. As we can see, although the trust values during attack stages vary across devices, all of them have trust values below the learned threshold when their network traffic flow data was captured from the attacked dataset.

Conclusion and Future Work

Vulnerable IoT devices increase the risks of attacking smart homes and unauthorized leakage. We believe that security and privacy services in IoT systems can be optimized by our fog trust scoring model deployed as a part of the FIoT middleware in a smart home gateway. Through this work, we showed that it is possible to move towards the unified treatment of detecting cyber attacks on smart home IoT devices.

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References

[1] R. Xu, Q. Zeng, L. Zhu, H. Chi, X. Du and M. Guizani, ”Privacy Leakage in Smart Homes and Its Mitigation: IFTTT as a Case Study,” *IEEE Access*, Vol. 7, pp. 63457-63471, 2019.

[2] “Security: The Vital Element Of The Internet Of Things,” CISCO, Mar. 2015. https://www.cisco.com/c/dam/en_us/solutions/trends/iot/vital-element.pdf

[3] Pymnts, “Wyze Smart Device Co Leaks 2.4M Customers’ Data,” PYMNTS.com, 30-Dec-2019. [Online]. Available: https://www.pymnts.com/news/security-and-risk/2019/wyze-smart-device-co-leaks-2-4m-customers-data/.

[4] A. Sivanathan, H. Gharakheili, F. Loi, A. Radford, C. Wijenayake, A. Vishwanath and V. Sivaraman, ”Classifying IoT Devices in Smart Environments Using Network Traffic Characteristics”, *IEEE Trans. on Mobile Computing*, Aug, 2019.

[5] Y. Amar, H. Haddadi, R. Mortier, A. Brown, J. Colley, A. Crabtree, “An Analysis of Home IoT Network Traffic and Behaviour” *arXiv:1803.05368*, 2018.

[6] D. Lo, C. Cho, C. Tan, R. Li, “Identifying unique devices through wireless fingerprinting” *ACM WiSec*, pp. 46-55, 2008.

[7] M. Lyu, D. Sherratt, A. Sivanathan, H. Gharakheili, A. Radford, V. Sivaraman. “Quantifying the reflective DDoS attack capability of household IoT devices” *ACM WiSec*, pp. 46–51, 2017.

[8] M. Nobakht, C. Russell, W. Hu and A. Seneviratne, “IoT-NetSec: Policy-Based IoT Network Security Using OpenFlow” *IEEE PerCom Workshops*, pp. 955-960, 2019.

[9] C. Bradley, S. El-Tawab and M. H. Heydari, “Security analysis of an IoT system used for indoor localization in healthcare facilities,” 2018 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, 2018, pp. 147-152.

[10] A. Hamza, H. Habibi Gharakheili, T. Benson, V. Sivaraman, “Detecting Volumetric Attacks on IoT Devices via SDN-Based Monitoring of MUD Activity”, *ACM SOSR*, USA, Apr 2019.

[11] O. Alrawi, C. Lever, M. Antonakakis and F. Monrose, “SoK: Security Evaluation of Home-Based IoT Deployments,” *IEEE Symposium on Security and Privacy (SP)*, pp. 1362-1380, 2019.

[12] S. Keoh, S. Kumar, and H. Tschofenig, “Securing the internet of things: A standardization perspective,”*IEEE Internet of Things Journal*, Vol. 1, no. 3, pp. 265-275, June 2014.

[13] A. Sivanathan, D. Sherratt, H. H. Gharakheili, A. Radford, C. Wijenayake, A. Vishwanath, V. Sivaraman, “Characterizing and classifying IoT traffic in smart cities and campuses,” *IEEE INFOCOM Workshops*, pp. 559-564, 2017.

[14] D. Kumar, R. Paccagnella, P. Murley, E. Hennenfent, J. Mason, A. Bates, and M. Bailey, “Skill squatting attacks on amazon Alexa,” *USENIX Security Symposium*, pp. 33–47, 2018.

[15] [Online] Available at: https://www.cloudflare.com/learning/ddos/what-is-a-ddos-attack/ [Accessed 24 February 2020].

[16] L. Desmond, C. Yuan, T. Pheng, R. Lee, “Identifying unique devices through wireless fingerprinting”, *ACM WiSec*, New York, NY, USA, pp. 46-55, 2008.

[17] V. Sivaraman, H. H. Gharakheili, A. Vishwanath, R. Boreli, and O. Mehani, “Network-Level Security and Privacy Control for Smart- Home IoT Devices,” *IEEE WiMoB Workshops (IoT-CT)*, Oct 2015.

[18] T. Yu, V. Sekar, S. Sheshan, Y. Agarwal, and C. Xu, “Handling a Trillion (Unfixable) Flaws on a Billion Devices: Rethinking Network Security for the Internet-of-Things,” in *ACM HotNets*, Nov 2015.

[19] V. Sivaraman, H. H. Gharakheili, A. Vishwanath, R. Boreli and O. Mehani, ”Network-level security and privacy control for smart-home IoT devices,” *IEEE WiMob* pp. 163-167, 2015.

[20] S. Bhattacharjee, M. Chatterjee, ”Trust based channel preference in cognitive radio networks under collaborative selfish attacks,” *IEEE PIMRC*, pp. 1502-1507, 2014.

[21] A. Jøsang, R. Ismail, C. Boyd, A survey of trust and reputation systems for online service provision, *Decision Support Systems*, Vol. 43(2), pp. 618-644, 2007.

[22] A. Parmisano, S. Garcia, M. Erquiaga, ’IoT-23 Dataset: A labeled dataset of Malware and Benign IoT Traffic.’, *Avast-AIC laboratory, Stratosphere IPS, Czech Technical University (CTU)*, Prague, Czech Republic, 2019.

[23] “NAT Traversal for IP Video Surveillance Application,” Mistral Solutions. [Online]. Available: https://www.mistralsolutions.com/articles/nat-traversal-ip-video-surveillance-application/.

[24] [Online]. Available: https://infosniper.net/.