IoT-KEEPER: Securing IoT Communications in Edge Networks

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Abstract

The increased popularity of IoT devices have made them lucrative targets for attackers. Due to insecure product development practices, these devices are often vulnerable even to very trivial attacks and can be easily compromised. Due to the sheer number and heterogeneity of IoT devices, it is not possible to secure the IoT ecosystem using traditional endpoint and network security solutions. To address the challenges and requirements of securing IoT devices in edge networks, we present IoT-KEEPER, which is a novel system capable of securing the network against any malicious activity, in real time. The proposed system uses a lightweight anomaly detection technique, to secure both device-to-device and device-to-infrastructure communications, while using limited resources available on the gateway. It uses unlabeled network data to distinguish between benign and malicious traffic patterns observed in the network. A detailed evaluation, done with real world testbed, shows that IoT-KEEPER detects any device generating malicious traffic with high accuracy (≈0.982) and low false positive rate (≈0.01). The results demonstrate that IoT-KEEPER is lightweight, responsive and can effectively handle complex D2D interactions without requiring explicit attack signatures or sophisticated hardware.

Keywords: IoT, Network, Security, Privacy, Activity Detection, Clustering, Anomaly Detection

1. Introduction

IoT-enabled automation systems have opened homes and industrial environments to countless new threats [1, 2]. There are several reasons for the sad state of IoT device security. IoT development teams often work without sufficient resources and under strict time constraints. These factors make it tempting for development team to cut corners, for example, by re-using unverified code snippets, insecure third-party libraries and not following secure software development practices [3, 4, 5]. These, and several other factors, result in production of inherently vulnerable devices for consumer markets.

The number of device specific exploits is constantly increasing due to growing number of IoT installations in small office, home office (SOHO), and enterprise networks. The adversaries can also re-use existing exploits from PC-platforms against IoT devices running a stripped down version of Linux or Windows as device firmware. Moreover, a vast majority of the IoT devices are connected to SOHO networks with no security in place except for the network address translation (NAT), which is done on the gateway. On several occasions, attackers have been able to compromise these devices, installed deep inside SOHO networks, to launch extremely large scale attacks [6, 7].

Due to prevalence of insecure IoT devices, network owners can no longer rely on the assumption that all devices in their network are well-behaving and trustworthy [8]. While this, to some extent, applies to every network, it is a particular concern in SOHO environments where the network owners do not have the know-how or resources to improve security. This, together with the fact that IoT devices are rarely updated [9], makes it probable that some devices in the network will, eventually, get compromised by an attacker.

There are three key solutions commonly used to secure PC and mobile devices: software updates, endpoint security solutions, and network-based security solutions. However, there are numerous reasons that these solutions cannot be used for securing IoT devices. Firstly, in most cases, there is limited, if any, product life-cycle support available for IoT devices, as the manufacturers do not provide regular firmware updates or security patches for these devices [10, 11].

Secondly, it is not possible to develop effective endpoint security solutions, such as anti-malwares, due to lack of firmware support, software APIs and limited resources available on IoT devices.

Securing network communications is a practical solution for securing IoT devices because these devices require constant network connectivity for their operations. It is also easier to gain network access to user devices, compared to
physical access. Traditional network security solutions offer limited support for securing IoT because these solutions mainly rely on traffic signatures for anomaly detection and it is practically infeasible to obtain enough labeled data from heterogeneous IoT devices, to generate these signatures. High deployment and operational costs of network security solutions is also a limiting factor in the use of existing network security solutions for securing SOHO and small enterprise networks.

Various techniques have been proposed to detect anomalies in network traffic using machine learning [12, 13, 14]. The applicability of these techniques depends on how accurately the classification model can capture given devices’ benign network behavior and use to it identify malicious traffic produced by that device. It is also challenging to keep these classification models up-to-date, as the devices’ network behavior can change substantially due to firmware updates and configuration changes.

The aim of this work is to propose a system addressing the challenges and needs of securing IoT in SOHO and enterprise networks. Such a system should actively monitor the network to identify and block any malicious traffic flows. It should maintain an up-to-date classification model detecting anomalies in network behavior of connected devices. The system needs to be lightweight and cost-efficient to support wide-scale deployments using only limited hardware resources. It should be scalable to support SOHO and enterprise scale deployments. Lastly, the system should ideally have high sensitivity, for identifying any malicious traffic, and low fall-out, to prevent false alarms.

In the light of these requirements, we propose IoT-Keeper, a novel system capable of classifying network traffic in real-time using semi-supervised machine learning techniques. IoT-Keeper monitors all traffic flows within and across the network. It identifies a device’s malicious behavior using the previous network activity of that device. In order to secure other devices in the network, IoT-Keeper uses adhoc overlay networks to limit network access for any device generating malicious traffic.

IoT-Keeper uses fuzzy C-Mean clustering and fuzzy-interpolation scheme to identify malicious network traffic. This technique is lightweight enough to allow deployments using single-board computers, for example Raspberry-PI, making IoT-Keeper cost-efficient and easy to deploy. Given the challenges of collecting labeled data, the classification algorithm was developed to work with unlabeled traffic data. This classification model can be represented as a set of rules, making it easier to share across multiple nodes, and improve scalability of the system.

This work demonstrates how a simple yet efficient classification algorithm, when combined with sophisticated feature analysis, enables us to successfully classify network traffic, using only limited hardware resources. Consequently, IoT-Keeper can be realized using legacy hardware.

More specifically, our contributions are:

- Design and implementation of IoT-Keeper, a novel end-to-end solution, capable of blocking any malicious network activity
- A simple and lightweight mechanism for dynamically enforcing network access control, at per-device, per-destination granularity, using adhoc overlay networks.
- Detailed study of individual features and their relative importance to formulate a set of most useful features for network traffic classification.
- A thorough investigation of IoT-Keeper performance using a real world testbed with 40+ devices. The evaluation results demonstrate that the proposed system is able to identify various types of network attacks, with high accuracy (0.982) and few false alarms (0.01), without any significant impact of user experience (latency increment ≈ 1.8%).

**Organization:** The rest of this paper is organized as follows. Section 2 introduces the threat model and challenges faced in securing IoT ecosystems. Section 3 describes the design and architecture of proposed system in detail. In Section 4, we present the techniques developed for feature engineering and anomaly detection. Section 5 describes the process of collecting dataset, used for training and evaluation of the proposed system. In Section 6, we present the evaluation of IoT-Keeper, in terms of performance achieved for detecting anomalies, network throughput and system efficiency. In Section 7, we revise the current state of the art for securing IoT ecosystem. Section 8 discusses possible shortcomings of the proposed solution. Finally, we present our conclusive statement about this work in Section 9.

## 2. Background

This paper refers to any network, where user devices are connected to get Internet access, as edge network, including SOHO and enterprise networks. A device with network connectivity and some sensing support can be referred to as connected or IoT device. This definition covers a wide range of devices, which can be divided into two categories:

- **Single-purpose devices:** include resource constrained devices such as sensors, appliances, with limited or dedicated functionality. Users manage and interact with these devices using a smartphone or tablet device.
- **Multi-purpose devices:** include high end devices such as smartphones and PCs, with better hardware resources. These devices support endpoint security solutions and device diagnostic tools. Due to access to sensitive user information and much larger attack surface, numerous sophisticated attacks have been developed to compromise such devices.
For the sake of simplicity, the remainder of this paper will refer to any of these two types of devices as an IoT device or simply device. These devices require network connectivity for majority of their operations. We divide the network communications of these devices into two categories.

- **Device-to-Device (D2D) communications**: This category includes network communications among the devices connected to same network. These communications usually occur within a single broadcast domain.

- **Device-to-Infrastructure (D2I) communications**: This category includes network communications between user devices and remote destinations. A remote destination can be any device or service operating in a different network or broadcast domain.

Unless specified otherwise, the rest of paper refers to both these types of communication as network communication.

Some single-purpose devices use low-power communication protocols, such as Bluetooth-LE (BLE) or Zigbee, to communicate with their respective IoT hub. The hub then communicates with respective cloud service(s) via wired or wireless network. As a result, the network traffic to and from the hub gives a fairly accurate representation of the D2I communications of the IoT devices, connected to the hub.

We now discuss the threat model for IoT ecosystem and the challenges faced in securing the networks where these IoT devices are connected.

2.1. Threat Model

Edge networks typically contain a mixture of single-purpose and multi-purpose devices. These networks are set up using a single gateway, to provide Internet access to all connected devices. The gateway offers basic security features such as, MAC/IP filtering. However, these features are not generally configured by users [11]. In case there is any intrusion detection system or firewall installed in the network, it only filters incoming and outgoing traffic, and treats all connected devices within the network as secure and trusted.

With IoT devices, this assumption about the trustworthiness of the devices does not hold, because it is fairly easy to exploit the vulnerable IoT devices, and thus gain access to the local network [15, 16]. Owing to common network setups, once an adversary is within the network, it gets unwarranted access to perform any type of attack against other devices in the same network. These attacks can be categorized as:

1. **Network scanning**: These attacks are used to recognize any TCP and UDP services that run at target hosts and to identify what kind of traffic filtering is done in the network. Network scanning can also be used to identify the firmware that is running on a target. These attacks are generally used to scan target nodes before launching dedicated attacks against the scanned targets. Commonly used variants of network scanning attacks include address-sweep, port-sweep, and port-scan attacks.

2. **Privilege escalation**: Once the target is identified and scanned, the adversary tries to gain privileged access to it, in order to deploy malicious code. Many IoT devices use stripped down Linux as firmware and, therefore, attacker may try to invoke shell to gain root access. Attacker can also use factory-default credentials or device specific exploits to gain privileged access. Upon success, attacker is able to upload malicious code and perform desired state changes to compromise the target node.

3. **Man-In-The-Middle (MitM)**: An adversary, connected to user network, can snoop-in on and interrupt all traffic in the network. It can use the communication patterns of legitimate user devices to conduct replay attacks. For example, an adversary can re-play traffic intercepted from communication between smartphone and garage door sensor, to later open garage door without users knowledge. MitM attacks have serious security and privacy implications, as they can be used to steal user data and disrupt potentially critical devices [17].

4. **Data theft**: Health IoT, smart appliances, and similar devices collect a lot of data, which reveals a lot of information about their users. Typically, users do not have discrete control over how this data is collected and transmitted [18]. An attacker can compromise user devices to steal this data and use it for targeted attacks.

5. **Botnets**: Botnets are generally comprised of infected devices installed inside edge networks [19, 12]. These devices maintain normal state of their operations until a command & control server instructs them to launch an attack against specific target(s). Distributed Denial of Services (DDoS) attacks are a common example of how seemingly benign user devices are used to launch attacks at unprecedented scales [7, 20].

The goal of IoT-Keeper is to identify and block any variants of the aforementioned attacks in edge networks. More specifically, IoT-Keeper presumes that, for a given device, any deviation from its benign behavior is motivated by malicious intent. Based on the type of attack the device was executing, network access restrictions are setup to limit the network activity of compromised device. This way, IoT-Keeper is able to block any compromised device from launching attacks against local or remote targets.

2.2. Challenges for Securing IoT

Conventional network and endpoint security solutions fall short in addressing the challenges of securing IoT
ecosystem for a number of reasons. We now go through some of these.

Firstly, there is a huge diversity in IoT devices’ firmwares, software stacks and APIs. Given this heterogeneity among devices, it is very challenging to develop generic endpoint security solutions for IoT devices. Although there are endpoint security solutions available for multi-purpose IoT devices, these solutions are not commonly used [21, 22]. There have been reports of incidents where endpoint security solutions could not detect smartphone applications, which were involved in stealing user data or performing similar attacks [23]. This heterogeneity also affects the network traffic patterns of the devices, making it infeasible to collect and maintain traffic signatures databases, which are used by signature-based network security solutions [24, 25].

Second challenge is related to the communication patterns of the IoT devices. Because IoT devices often need to interact with other devices in the same network, the IoT devices cannot be completely isolated from each other. However, simultaneously, one cannot blindly trust every device in the local network. Thus, it is not enough to simply protect the perimeter of the local network, but instead, also the internal traffic would need to be monitored.

Thirdly, traffic analysis should be performed on network gateways to address privacy and latency concerns. Typical SOHO networks are set up using low-cost network gateways with constrained hardware resources. This means that the in order to perform traffic classification on these gateways, classification algorithms should be lightweight. Furthermore, these gateways should support automated configuration because it is clear that having a dedicated administrator for every edge network is an unrealistic requirement [25]. These devices should not require much manual configuration and any required configuration changes should be easy for the users to make — it is well known that due to poorly designed interfaces and lack of support for automated configuration, the networks are rarely configured by users [10, 25, 26].

Based on this discussion, the basic set of requirements for a security solution addressing the challenges posed by IoT can be summarized as follows.

- It should be easy to deploy and operate with minimal manual effort. Meanwhile, it should be low cost with limited resource footprint.

- It should be able to monitor inter as well as intra-network communications to detect various (benign and malicious) types of network traffic generated by connected devices.

- Traffic analysis should be performed close to edge networks to immediately detect and block any attacks. Meanwhile, it should be easy to share the data needed to detect these attacks, among network gateways.

3. System Design

IoT-Keeper consists of two primary components, Keeper Gateway and Keeper Service, as shown in Fig. 1. Keeper Gateway is a redesigned gateway used to set up edge networks. It also performs traffic classification and security policy enforcement for traffic filtering. Keeper Service is a cloud service assisting various functionalities of Keeper Gateway. This two-tier design achieves low cost and high scalability, to provide enterprise-grade security at only a fraction of cost.

![Figure 1: IoT-Keeper architecture, where Keeper Gateway performs traffic monitoring and classification. Controller (1) is responsible for traffic management at OF switch (2), traffic classification, caching (3) and enforcement of security policies. Keeper Service (4) is used for support operations.](image)

3.1. Keeper Gateway

Keeper Gateway is a lightweight network gateway designed to be agnostic of the underlying hardware, such that it can be deployed using a WiFi access point [10] or single board computer, for example, Raspberry-Pi (R-Pi).

In principle, Keeper Gateway is a gateway used to setup edge networks. In addition to routing and switching, this gateway is responsible for traffic monitoring, anomaly detection, and policy enforcement to manage network access at per-device granularity. Meanwhile, the initial model training, state management, and remote administration is performed with the help of Keeper Service.

Keeper Gateway runs an SDN controller and Open vSwitch (OVS) to perform traffic monitoring, anomaly detection and traffic filtering. Other than the basic routing functions, the three key modules that are operated by the SDN controller are traffic monitoring, anomaly detection, and security policies enforcement. Monitoring module inspects all intra and inter–network traffic flows to maintain up-to-date information about the network behavior of all
devices connected to the network. Detection module uses the data from monitoring module to identify if any given traffic flow is malicious. The classification model, which is used to identify different types of traffic flows, is maintained by Keeper Gateway. Enforcement module is responsible for setting up network access control to restrict network activity of any device exhibiting anomalous network behavior. This module uses a set of security policies to generate flow table entries and deploy them at the OVS, to perform traffic filtering.

For every traffic flow, enforcement module looks for a relevant security policy from cache. If there are multiple matches, the most specific security policy is used for setting up flow table entries to handle the flow. Otherwise, if no relevant security policy is found, the detection module analyzes the traffic flow to identify its type. The result of analysis is cached in form of a security policy and respective flow table rules are deployed, by the enforcement module, at the switch handling given traffic flow.

In current description, both the controller and OVS run on the same gateway. However, IoT-Keeper architecture supports deployments where a single instance of Keeper Gateway manages multiple OpenFlow-enabled switches in the network. In such cases, traffic from all the switches will be classified and managed by the controller running on Keeper Gateway.

Caching

In general, majority of traffic in edge networks is destined to a handful of cloud services. In case of a new traffic flow, there is high probability that subsequent flows in the session are related to same network activity. The benign network activity for single-purpose IoT devices is also fairly limited.

By caching the security policies relevant to these frequent traffic flows, we can greatly reduce the number of traffic classification operations, thereby, reducing the latency experienced by users as well as limiting the resource consumption. The impact of caching on latency and resource consumption are discussed in detail in Sect. 6.3.

Caching can be implemented using hash table data structure, to achieve time and space complexity of $O(1)$ and $O(n)$ respectively. The storage consumption can further be limited by associating an expiry time to each security policy stored in cache. This expiry time is refreshed every time security policy is used to set up filtering for some traffic flow. Once this time period expires, security policy is removed from cache. The optimal choice for expiry time depends on the underlying network traffic patterns and storage capacity available for cache.

Management API

Unlike traditional gateways and routers, Keeper Gateway does not run a local web server for hosting gateway management portal. This design choice was made to reduce the attack surface. Setup and configuration changes are performed using a mobile application, which communicates with the gateway using low-power protocols such as BLE. This requires physical proximity of user to make any configuration changes to the gateway. The requirement of physical proximity bars any untrusted entity from accessing the management interface over the network. Sect. 3.3 discusses how the users can perform configuration changes, when they are connected to some other network.

3.2. Adhoc Overlay Networks

It is a common requirement for gateways and routers to support multiple networks for different kinds of devices connected to the network. Although it is possible to run multiple networks on legacy gateways using VLANs or multiple SSIDs, there is only a limited number of VLANs and SSIDs supported by any router or access point available in market. It is difficult to automatically setup and manage the VLANs on router and gateways typically used to deploy edge networks. In case of multiple SSIDs, client devices need to (re)associate every time SSID configuration is updated, thereby, ruining the user experience. Therefore, it is not easy to achieve per device access control using legacy gateways.

IoT-Keeper uses adhoc overlay networks (AON), for creating multiple virtual networks, over a physical network. The number of AONs is not limited by hardware as they are set up dynamically by the enforcement module. The network restrictions defined for a given AON can be updated dynamically, without requiring any action from client devices. Figure 2 demonstrates how AONs work in practice.

![Figure 2: A single SSID is partitioned in 3 AONs, where (i) D1, D2 and D3 are fully isolated and can not communicate with any other device in the same network, (ii) devices in safe AON have full network access to Internet and other devices in same AON, but restricted access to devices in other AON, (iii) devices in suspicious AON are partially isolated and have limited access to Internet and other devices in same AON.](image)

With AONs, it is possible to set up access control on per-device granularity. For example, a smart fridge can be restricted to communicate only with its own cloud service and owners’ smartphone. AONs restrict the network

\[1\] Raspberry Pi supports 1 SSID using built-in WLAN interface. Commercially available routers for non-enterprise networks can support upto 8 SSIDs.
access for suspicious device(s) in a way that given device retains its Internet access, but cannot attack any local or remote targets.

3.3. Keeper Service

Keeper Service is designed as a support service for Keeper Gateway operations. It does not perform traffic classification for edge networks but it hosts different services to enable seamless operations of Keeper Gateway.

The design choice of using a remote service is motivated by cost efficiency and scalability. This approach allows us to use data from multiple sources and perform various analysis to train initial classification model, used by Keeper Gateway. It also provides support for operating a multitude of services to enhance Keeper Gateway functionalities. Keeper Service can be used to perform sophisticated analysis and operate middleboxes for re-routing suspicious traffic from edge networks, through these middleboxes. This service can be deployed within user premises or provided by a third party.

Keeper Service is primarily responsible for maintaining up-to-date classification model for bootstrapping traffic classification on the Keeper Gateway. It also supports state management and remote administration of Keeper Gateway.

Initial classification model

When Keeper Gateway is set up for the first time, it recieves the initial classification model from Keeper Service. This model is trained by Keeper Service, using the data collected from various sources including network logs, malware databases [27], and public vulnerability databases (CVE [28] and CWE [29]). Keeper Gateway initially uses this model for anomaly detection, and continues to improve it using the data collected from local network traffic.

The use of same model training technique by both Keeper Service and Keeper Gateway improves the interoperability, in such a way that Keeper Service and Keeper Gateway can share the trained models with each other. The trained models are shared in form of a set of rules containing feature value distributions and corresponding labels (described in Sect. 4.6). This representation is compact and thus can be easily shared among nodes without incurring significant network overhead.

State management

In order to support stateful recovery, Keeper Service periodically backs up the state of Keeper Gateway, in fully encrypted form. The state information includes classification model data, security policy cache and gateway configurations. Using this data, Keeper Gateway is fully restored at any required state. Encryption and trusted platform module can be used to ensure that the state can only be restored on the same Keeper Gateway that was backed up [30, 31]. To support rapid deployment and recovery, the state can be restored or synchronized across multiple gateways simultaneously.

Remote administration

Since users need to be in physical proximity of Keeper Gateway to perform any configuration changes, any users connected to remote networks can perform update gateway configuration using the web-portal offered by Keeper Service. Any configuration changes made on web-portal are installed at respective Keeper Gateway, deployed in the edge networks, by Keeper Service. The configuration changes made through web portal are validated to make sure that they do not compromise Keeper Gateway functioning, by switching it to insecure state. The additional verification prevents any scenarios where an attacker gets access to user account or compromises the Keeper Service, to configure all Keeper Gateway devices and disrupt their functioning.

3.4. Communications with user

A key requirement of designing usable security solutions is finding the right balance in user experience and security. IoT-Keeper achieves this balance by maintaining minimal network access for suspicious device, so that they can continue their normal operations\(^2\), but cannot perform any attacks.

IoT-Keeper automatically detects any attacks and sets up counter measures to prevent these attacks, without user involvement. However, it is important to notify the users about blocked threats and the state of their network. For this purpose, IoT-Keeper supports two types of notifications. Passive notifications simply inform users about the network activity, while actionable notification require users to take an action, for example, reconfigure the device. A detailed discussion on the appropriate level of nagging and notification mechanism is outside the scope of this paper.

4. Methodology

4.1. Feature extraction

IoT-Keeper is designed for networks with heterogeneous device base and no dedicated network security devices. It is safe to assume that there are no device logs available from most single-purpose IoT devices. Therefore, IoT-Keeper heavily relies on feature extracted from network traffic data, to differentiate between benign and malicious network activity.

A key challenge in feature extraction for an online traffic classification technique is to swiftly compute the statistics over incoming data (packet) stream, where packet arrival

\(^2\) Our analysis reveals that \(\geq 95\%\) traffic from benign IoT device is HTTP/HTTPS traffic to their cloud service, which will not be blocked, so IoT device can maintain its normal operation.
rates is very high. To address this, we incrementally compute a set of statistics, including number of observations $N$, sum of observations $S_o$, and sum of squares of observation $S_{sq}$, for all traffic streams. Using these statistics, we can compute mean and standard deviation for the set of observations, as shown in Eq. 1.

$$\mu = S_o/N \quad \sigma = \sqrt{|S_{sq}/N - (S_o/N)^2|} \quad (1)$$

Table 1 lists the 44 attributes obtained from network metadata and device logs. We calculate the three aforementioned statistics for all 44 attributes to get the final feature vector $\vec{F}$, where $\vec{F} \in \mathbb{R}^n \wedge n \leq 132$. The statistics can be summarized on per device basis using source and destination MAC, IP and ports. These statistics allow us to calculate the divergence of devices’ behavior, over a specific time window, from its baseline (benign) behavior, to detect any anomalies.

In contrast to existing techniques [32], which use time-based aggregation to aggregate same host, same service features, we use connection based aggregation. The key limitation of time-based aggregation is that it falls short in detecting attacks with a wait mechanism, where a random delays are added in-between successive connection attempts. In comparison, connection-based aggregation aggregating the features over $n$ latest connections allows us to accommodate any random delays between successive connections.

Table 1 lists six attributes retrieved from device logs. These attributes contain information about any login attempts, SSH connections and service discovery requests. Such information can be useful to identify the sub-type of malicious traffic flows identified by anomaly detection technique. In order to correlate the data from device logs with network traffic data, time must be synchronized across the network. Time synchronization among all connected devices can be achieved using protocols such as NTP. In case no such service is running in the network, time difference between network and device logs can be manually resolved.

### 4.2. Feature Analysis

We study the variance and modality of each feature to identify its contribution to anomaly detection model. Any features that do not contribute significantly to the clustering and classification process are pruned off. Reducing the number of features helps in speeding up the classification process and reducing the resource footprint of clustering and anomaly detection scheme.

Initially, we plot cumulative distribution function (CDF) for each feature, to study its variance. Figure 3 shows CDF plots for a few of the features corresponding to connections made by any device. For example, Fig. 3a shows the distribution for number of unique destination IPs contacted by devices in the network. It can be observed that this distribution is not Gaussian but heavy tailed with majority of probability mass lying in smaller values. This distribution reveals that more than 70% of the devices connect to fewer than 20 unique destination IPs. On the other hand, tail of distribution contains data points where a single device may connect to more than 500 unique destinations. Similarly, Fig. 3d shows that more than 75% of the devices do not generate any SSH traffic. However, there are some devices generating a large volume of SSH traffic, indicating presence of suspicious activity in the network.

The data points in the tail of distributions are of primary importance for anomaly detection since they capture anomalous behaviors. It is important to capture this information as it helps in differentiating anomalies from benign network behavior, during clustering.

When we jointly study the distribution of different features, it reveals interesting details about semantics of various attacks. For example, during a fuzzing attack, when an attacker tries to login to open services on target node with brute-force, the attack is reflected in network traffic with a large number of connections between same source and destination nodes. Meanwhile, device logs from target node show a large number of failed login attempts, proving the hypothesis that an attack is undergoing against target node.

Further analysis revealed that during such brute-force attacks, if the few initial login attempts fail, there is a high probability that attack will not succeed. This observation shows that users who change the factory default passwords choose reasonably unique passwords, which are not easy to crack using traditional dictionary or brute-force attacks. However, this claim cannot be made with absolute certainty because of limited scope of dataset.

The study of feature value distributions also reveals possible correlations among different features. For example, as the attacker scans a target node, both total number of connections initiated by the attacker node and number of connections between source (attacker) and destination (target) node increases. These correlations help us to identify and remove features containing redundant information.

### 4.3. Feature reduction

We use correlation-based feature selection (CFS) and deviation method to identify and remove any features which contain redundant information and do not contribute significantly to the anomaly detection scheme.

CFS identifies strongly correlated features by measuring their linear dependencies. The dependencies are calculated using Pearson correlation coefficient $R$ because it provides fairly accurate results with bounded feature value ranges for datasets of fairly large size. Based on the value of $R$, CFS discards one of any two features which are strongly co-related, since such two features contain redundant information and keeping both features do not offer value for anomaly detection. Figure 4 shows that majority of features in our feature set $\vec{F}$ are linearly independent. How-
ever, some of the features, such as $f_1 - f_6$, may contain redundant information and can be removed from $\vec{F}$.

In order to make sure that no feature over-influences clustering, all feature values are normalized to range $[0, 1]$. After clustering, normalized feature score are computed, for each feature, in all clusters. Any features, such as REJ errors, with same scores (within a defined tolerance) in multiple clusters are considered non-contributing feature and removed from the final feature set.

### 4.4. Clustering

We use fuzzy C-mean (FCM) clustering algorithm to partition the data points based on their mutual likeliness. During clustering, initially a membership value is assigned to all data points $X_j$ ($j = 1, 2, ..., n$), for all clusters $C_i$ ($i = 1, 2, ..., c$). Each data point $X_j$ is represented as $(f_j^{(1)}, f_j^{(2)}, ..., f_j^{(k)})$ where $f_j^{(k)}$ is value for $k$th feature in $X_j$ and $1 \leq k \leq n$. $n = \text{len}(\vec{F})$.

The membership value for $X_j \in C_i$ is given as $\mu_{ij}$, where $0 \leq \mu_{ij} \leq 1$, $\sum_{i=1}^{c} \mu_{ij} = 1 \quad \forall 1 \leq i \leq c \land 1 \leq j \leq n$. The membership value $\mu_{ij}$ for each data points and cluster centers $V_i$ for each cluster are optimized using Eq. 2 and Eq. 3 respectively, in order to minimize objective function given in Eq. 4.

$$\mu_{ij} = \left( \sum_{d=1}^{c} \left( \frac{\|V_i - X_j\|}{\|V_d - X_j\|} \right)^{2(m-1)} \right)^{-\frac{1}{m-1}}, \quad 1 \leq i \leq c \land 1 \leq j \leq n$$ (2)

$$V_i = \frac{\sum_{j=1}^{n} (\mu_{ij})^{m} \times X_j}{\sum_{j=1}^{n} (\mu_{ij})^{m}}, \quad 1 \leq i \leq c \land 1 \leq j \leq n$$ (3)

$$J_m = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{m} \|V_i - X_j\|^2$$ (4)

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Table 1: List of attributes extracted from network and device metadata

| Type                  | Feature                                                                 |
|-----------------------|-------------------------------------------------------------------------|
| Source, Destination   | [Total, Unique] destination IP addresses                                |
| Connection counters   | [Total, Unique] source ports, destination ports, connections, (same source, same destination, same service) connections, connection durations (binned) |
| Packet counters       | ARP, LLC, IP(v6), ICMP(v6), EAPoL, TCP(v6), UDP(v6), HTTP, FTP, HTTPS, DHCP, (M)DNS, NTP, Router Alert, (SYN, REJ) (errors), Urgent, Padding |
| Data (binned)         | Total data, source to destination (SRC2DST) data, destination to source (DST2SRC), packet size |
| Authentication        | [Successful, Failed] login attempts to [SSH, Service, Device]            |

Figure 3: CDF plots for a small subset of features corresponding to network behavior of user devices. These distributions are observed in the dataset used for training and evaluation purposes.

Figure 4: Correlation map plot depicting linear dependence among a subset of features from $\vec{F}$.

Using deviation method, 1-length frequent items sets are mined from the feature set to obtain $F_i = \{V_1, V_2, ..., V_j\}$, where $V_j = \{f_i; 1 \leq i \leq n\}$, $\text{supp}(f_i) \geq m$, $m$ is minimum support and $f_i$ is frequent item. The deviation range for each feature is calculated as $D_{V_j} = [f_{\max}, f_{\min}]$, where $f_{\max} = \max(f_j)$ and $f_{\min} = \min(f_j)$, for all benign and malicious traffic classes. If the deviation range of a feature is similar for all classes, the feature is considered non-contributing feature and removed from the feature set.
where $m$ is fuzziness index [33] and \( \|V_i - X_j\| \) is the Euclidean distance between cluster center $V_i$ (for cluster $C_i$) and data point $X_j$.

A label is assigned to each cluster based on normalized feature scores observed in the given cluster. These labels correspond to different types of benign and malicious network traffic. Each cluster can be represented as a rule, where feature scores represent antecedent variables and cluster label is the consequent variable. The set of rules, obtained as output of clustering process, is used by FIS to perform anomaly detection.

4.5. Parameter Selection

The choice of number of clusters $i$ can affect the performance of anomaly detection technique. Therefore, we both do statistical testing with $i$ and vary them using elbow method and average silhouette heuristic [35]. These two methods provide a measure of global clustering characteristic. For elbow method, within-cluster-sum-of-distances (WCSD) is calculated using Eq. 5, where $b$ is the number of clusters, $S_i$ is the set of data points belonging to $i^{th}$ cluster, and $x_{ki}$ is the $k^{th}$ variable of $V_i$.

\[
WCSD = \frac{c}{i=1} \sum_{j \in S_i} \sum_{k=1}^{p} \|x_{ki} - x_{ji}\| \tag{5}
\]

Silhouette heuristics are calculated using Eq. 6, where $a(x) = \frac{1}{k} \sum_{j=1}^{k} \|x - p_j\|$, $p_j \in C_i \land x \in C_i$. Similarly, $b(x) = \frac{1}{k} \sum_{j=1}^{k} \|x - p_k\|$, where $p_k \in C_i' \land C_i' \text{ is the closest \(k^{th}\) neighboring cluster for } x \text{ such that } C_i' \subseteq C_i \subseteq C$ with $\min\{\|x - V_j\|\} \land C_i \subseteq C \land x \not\in C_i$. Figure 5 shows that both elbow and silhouette method suggest $i = 17$ as optimal value for $i$.

\[
s(x) = \frac{(b(x) - a(x))}{\max(a(x), b(x))} \tag{6}
\]

We also studied gap statistic method [36] to get a statistical formulation of WCSD and silhouette statistics. In general, the optimal value for $i$ should maximize the gap statistic as well as silhouette values, while minimizing WCSD. Using 1-standard-error method [36], gap statistics analysis suggests $i = 17$ as optimal number of clusters for given scenario.

4.6. Anomaly detection

IoT-Keeper uses Fuzzy interpolation scheme [37, 38] (FIS) to identify the type of given traffic flow in the network. FIS uses the sparse fuzzy rule base consisting of $n$ rules ($n = c$), obtained from clustering, to identify the type of traffic flows in the network. The set of rules is represented as.

\[
\text{Rule 1: } \text{if } f_1 \in A_{11}, f_2 \in A_{21}, \ldots, f_k \in A_{k1} \ldots f_k \in A_{k1} \Rightarrow y \in O_1
\]

\[
\text{Rule 2: } \text{if } f_1 \in A_{12}, f_2 \in A_{22}, \ldots, f_k \in A_{k2} \ldots f_k \in A_{k2} \Rightarrow y \in O_2
\]

\[
\vdots
\]

\[
\text{Rule Q: } \text{if } f_1 \in A_{1Q}, f_2 \in A_{2Q}, \ldots, f_k \in A_{kQ} \ldots f_k \in A_{kQ} \Rightarrow y \in O_Q
\]

Observation: $f_1 \in A_{1*}, f_2 \in A_{2*}, \ldots, f_k \in A_{k*}$

\[
\text{Conclusion: } y = O^{*}
\]

where $R_i (1 \leq i \leq Q)$ is $i^{th}$ rule generated from cluster $C_i$, $A_{ki}$ and $O_i$ are triangular fuzzy sets for $k^{th}$ antecedent feature $f_k, 1 \leq k \leq h$ and consequent variable $y$ respectively. For any new observation, $A_{k*}$ and $O^{*}$ are triangular fuzzy sets for antecedent and consequent variable obtained as a result of interpolation of spare fuzzy rule base.

A fuzzy triangular set $A$ is represented using three characteristic points $a, b, c$, where $b$ is center point with maximum membership value and $a, c$ are left, right points respectively, with maximum membership value. The characteristic points $a_{ki}, b_{ki}, c_{ki}$ for fuzzy set $A_{ki}$ of $k^{th}$ antecedent feature $f_k$ in rule $R_i$ are calculated as:

\[
b_{ki} = f^{(k)}_q, \quad \text{where } \mu_{iq} = \max_{1 \leq j \leq n} \mu_{ij}, \tag{7}
\]

\[
a_{ki} = \frac{\mu_{ij} \times f^{(k)}_j}{\sum_{j=1,2,\ldots,n} \mu_{ij} \times f^{(k)}_j}, \quad \tag{8}
\]

\[
c_{ki} = \frac{\mu_{ij} \times f^{(k)}_j}{\sum_{j=1,2,\ldots,n} \mu_{ij} \times f^{(k)}_j}, \quad \tag{9}
\]

where $b_{ki}$ has membership value of 1 and $a_{ki}$ and $c_{ki}$ have membership value of 0. $f^{(k)}_j$ is the $k^{th}$ feature’s value in sample $X_j$ with $1 \leq k \leq h$. The defuzzified value of a triangular set $A$ is calculated as

\[
D_f(A) = \frac{(a + 2 \times b + c)}{4} \tag{10}
\]

Similarly, the characteristic variable $a_i, b_i, c_i$ for consequent variable $B_i$ for $R_i$ are calculated as:

\[
b_i = O_q, \quad \text{where } \mu_{iq} = \max_{1 \leq j \leq n} \mu_{ij}, \tag{11}
\]

\[
a_i = \frac{\sum_{j=1,2,\ldots,n} \mu_{ij} \times O_j}{\sum_{j=1,2,\ldots,n} \mu_{ij}}, \quad \tag{12}
\]
where $O_j$ is expected output class for $X_j$, and $1 ≤ i ≤ c$. The membership value for input feature $f_j^{(k)}$ is $\mu_{A_k,i}(f_j^{(k)})$, where $\min_{1 ≤ k ≤ h} \mu_{A_k,i}(f_j^{(k)}) > 0$, $1 ≤ i ≤ p$, and $p$ is the number of activated fuzzy rules. The inferred output $O_j^*$ based on fuzzy rules activated by $f_j^{(1)}, f_j^{(2)}, \ldots, f_j^{(h)} ∈ X_j$ is calculated as,

$$O_j^* = \sum_{i=1}^{c} W_{i} \times D_f(B_i) \times \mu_{A_k,i}(f_j^{(k)})$$

$D_f(B_i)$ is defuzzified value for consequent fuzzy set, in $R_i$ activated by $X_j$ inputs and it can be calculated using Eq. 10. We calculate the weight $W_i$ of activated rule $R_i$, such that $0 ≤ W_i ≤ 1$, $\sum_{i=1}^{p} W_i = 1$, on the basis of input observations $x_1 = f_j^{(1)}, x_2 = f_j^{(2)}, \ldots, x_h = f_j^{(h)}$ as:

$$W_i = \left( \sum_{d=1}^{c} \frac{\left( \left| r^* - r_i \right| \right)^2}{\left| r^* - r_d \right|^2} \right)^{-1}$$

where $r^*$ is the input feature vector $(f_j^{(1)}, f_j^{(2)}, \ldots, f_j^{(h)})$ and $r_i$ is set of defuzzified values of $A_k$ in $R_i$. $(D_f(A_1,i), D_f(A_2,i), \ldots, D_f(A_k,i))$, $1 ≤ k ≤ h$.

The final inferred output is calculated as

$$O_j^* = \sum_{i=1}^{c} W_i \times D_f(B_i)$$

5. Dataset

We have deployed a real world testbed for data collection and system evaluation. The testbed consists of more than 40 consumer IoT devices including single-purpose and multiple-purpose devices. All devices mainly use wireless mode for network connectivity, while some devices also support wired connectivity as well. Some of the devices use BLE for device pairing purposes only. Other low-energy communication protocols such as Weave, Zigbee are mainly used by devices to communicate with IoT hubs. The set of common vulnerabilities found in these devices include factory-default, commonly-used login credentials, open, unfiltered ports, and terminal access without password.

The choice of multi-purpose devices such as phones and PCs, in the testbed is motivated by the fact that these devices constitute a large proportion of devices connected to edge networks. With access to much more sensitive information, smartphones and PCs are lucrative targets for attackers. Attackers exploit vulnerable IoT devices and use them to compromise high-end devices containing sensitive user data. Therefore, it is important to study the communications between single and multi-purpose IoT devices to detect any attacks.

Testbed Setup

The network setup used for data collection is shown in Fig. 6. In this setup, all devices were connected to Keeper Gateway, which is deployed using a Raspberry-Pi (R-Pi), and setup as a wireless access point using hostapd. It also runs a DHCP server and manages NAT for both wired and wireless network. Current setup uses public DNS server but a local DNS can also be set up. All incoming and outgoing traffic from both wired and wireless interfaces is collected using tcpdump. Any traffic filtering was performed using layer-2 addresses. During data collection, R-Pi was configured to drop all unfiltered outgoing traffic to prevent spread of malicious traffic on public Internet.

As mentioned before, all devices in the testbed support WiFi or wired connectivity. In case any device communicates to Internet via an IoT hub, using Weave, ZigBee or similar protocols, its D2I communications are monitored by capturing the network traffic generated by IoT hub.
Data collection

The data collection process spans three phases of device activity:

- **Setup**: This phase covers the network activity of a device when it is setup by the user for the first time.

- **Background**: This phase covers the network activity of a device during its normal operation, including the phase when it connects or disconnects from the network. The background activity may vary with the kind of device, for example, single-purpose devices may only generate heartbeat or status update messages, whereas, multi-purpose devices may periodically fetch application updates, generate notifications etc.

- **Activity**: This phase covers the network activity of a device when it is actively communicating with other entities in the network. The network traffic generated by device corresponds to user interactions or messages communicated with other devices. The network activity during this phase varies with the functionalities available in device. For example, Dlink power plugs support only on/off functions, whereas a security camera allows user to switch on/off video feed, change video quality etc.

To collect device setup phase traffic, we collected all traffic from the device itself, as well as the management device used to setup the device. The device was reset and booted from factory default state prior to every time it was setup. For most devices, the firmware was upgraded before concluding the setup. The background traffic was collected by setting up a device and leaving it in connected state for a given time interval. The duration of these intervals ranged from 10 minutes to 72 hours. To collect data for device activity, user repeatedly performed an action on the device over a period of time, with irregular wait intervals between repetitions. The data collection was performed for different types of actions supported by the device. During data collection, the management device was either connected to same network, as the IoT device itself, or a remote network. After every iteration of data collection activity, network setup was reset to recover virgin network state for subsequent iteration.

We assume every device to be inherently benign, therefore, the traffic it generates during standby and normal user interaction is considered its benign network behavior. Table 2 lists different types of network attacks used for collecting traffic traces of malicious network activity. These attacks are commonly observed in IoT and edge networks [39, 40, 41, 42, 43].

Table 2 gives a high level classification and description for different types of attacks. It also lists the tools which are used to simulate these attacks. The number of training samples indicate the traffic flows used for model generation, whereas evaluation samples show the number of traffic flows used for evaluation. In order to emulate real world deployments, the volume of traffic handled by IoT-Keeper during evaluation is much higher compared to the volume of traffic used to train the system. In addition to data collected from the testbed, we also use publicly available datasets for malicious IoT traffic [44].

6. Evaluation

6.1. System Implementation

The evaluation testbed uses a Raspberry PI model 3 to deploy Keeper Gateway and a Core-i5 machine with 32GB memory to deploy Keeper Service. Keeper Gateway runs Open vSwitch (OVS) [45] and Floodlight [46] based SDN controller, with self-implemented custom modules that are used to perform traffic monitoring, traffic filtering, state management, security policy enforcement and cache management. The feature engineering and anomaly detection schemes were implemented with Python. Both Keeper Gateway and Keeper Service use REST-APIs for communicating with each other.

Keeper Gateway was setup as a WiFi AP using hostapd module [47]. All wired and wireless interfaces are bridged to OVS, so that all network traffic is managed by Keeper Controller. In larger deployments, multiple OF switches are configured to use SDN controller running at the Keeper Gateway, for traffic management. During evaluation, no data was sent to Keeper Service and the initial classification model was trained using previously collected traffic data from the testbed.

\footnote{(10, 20, 30) minutes, (1, 2, 6, 10, 12, 24, 36, 72) hours}
| Classification Activity | Tool         | Description                                                                 | Evaluation samples | Training samples |
|-------------------------|--------------|------------------------------------------------------------------------------|--------------------|------------------|
| Scanning                | Port scan    | ZenMap, NMap                                                                  | 1243647            | 292092           |
|                         | Port         | ZenMap, NMap                                                                  | 953684             | 238421           |
|                         | Sweep        | ARPing, Skipfish                                                              | 824363             | 229173           |
|                         | Address      | Telnet                                                                       | 1389672            | 437418           |
| Botnet                  | Mirai        | Telnet                                                                       | 1706479            | 416619           |
| Privilege escalation    | ARP Poisoning| Arpspoof, EtterCap                                                           | 2356842            | 559211           |
|                         | Fuzzing      | PowerFuzzer, WFuzz, Python, Telnet                                           | 821468             | 195371           |
| Data Theft              | Data hijacking| Metasploit                                                                    | 1161347            | 304336           |
| Malware                 | Malware      | Metasploit                                                                    | 2801145            | 699543           |
| Denial of Service       | SYN          | Metasploit                                                                    | 3084492            | 671123           |
|                         | Flooding     | Python, scapy, Hynae, tls-dos, scapy                                          |                   |                  |

Table 2: Types of network attacks executed by compromised and malicious devices.

This testbed setup serves as a reference implementation of IoT-Keeper. Our implementation was not optimized for performance gains. Therefore, the system and network performance results may vary with different hardware and software stacks used for system implementation.

6.2. Anomaly Detection

We studied the performance of anomaly detection technique in terms of sensitivity and false positive rates (FPR). Sensitivity, also known as recall, gives a measure of reliability of our technique in correctly identifying the malicious traffic flows, whereas, FPR gives an estimation of false alarms raised by the system, when benign activity is flagged as malicious. Ideally, the FPR rate should be zero, producing no false alarms. The trade-off between FPR and false negative rate (FNR) may vary with different scenarios. In general, low FPR may be preferred as it improves user experience by preventing false alarms. However, highly sensitive installations may require low FNR, so that no malicious traffic goes undetected and compromise the whole network. Using IoT-Keeper, false positives do not significantly impact user experience because IoT-Keeper enforces (and removes) network restrictions for any device, while maintaining minimal network access for the device, allowing it to continue its normal operations. This enables us to target lower FNR as well, for better security, without negatively affecting user experience.

We consider two types of classification problems:

- **Binary-class problem:** Differentiating between benign and malicious network activity to detect anomalies.

- **Multi-class problem:** Identify the sub-type of malicious activity exhibited by the device.

The motivation to identify the sub-type of malicious activity is that it provides us more information that can be used to enforce different levels of network restrictions for any device. For example, a device executing a network scanning attack may only be allowed to access its respective cloud service, whereas, network access for a device stealing user data should be completely blocked. This paper does not focus on identifying the sub-types of benign activity.

Our evaluation shows that IoT-Keeper was able to achieve an accuracy of 0.982 with FPR= 0.01 and FNR= 0.02 for binary-class problem. It shows that our anomaly detection technique can differentiate between benign and malicious network activity with high sensitivity. Based on these results, it can be concluded that IoT-Keeper is able to successfully identify block any malicious activity in the network.

Table 3 shows the performance achieved for identifying different types of malicious traffic. The results show that IoT-Keeper can identify volumetric attack (generating large volumes of traffic) with high sensitivity (0.99) and
low FPR (= 0.02). The network scanning attacks, in general, are detected with an accuracy of 0.993 and f1-score 0.986. This performance is better than the performance achieved for identifying different variants of network scanning attacks.

In order to investigate this discrepancy, we study the feature value distributions in clusters representing these attacks. The feature value distributions represent the network behavior for different types of network activity. Therefore, if multiple network attacks have similar network footprint, the feature value distributions, observed in the clusters representing that traffic, will be overlapping. This overlap will result in misclassification. This phenomenon is prominent when we study different variants of network scanning attacks and it explains the relatively lower accuracies achieved for detecting variants of network scanning attacks. However, it should be noted that a network scanning attack, if it happens, is only misclassified as another network scanning attack. Since, the network restrictions for a device performing any type of network scanning attack are similar, the resulting security implications of these misclassification are negligible for given problem scenario.

Compared to volumetric attacks, it is difficult to detect a DoS attack because the network activity for these attacks is sporadic and difficult to distinguish from benign traffic. However, IoT-Keeper achieves good performance in detecting these attacks, which otherwise go undetected by anomaly detection systems.

Our analysis revealed that device logs can also be useful for identifying the sub-type of malicious traffic. For example, analyzing network traffic generated during fuzzing attack may register it as a network scanning or DoS attack. However, studying device logs reveals it was a fuzzing attack against particular service running on target host.

### Table 3: Performance achieved by IoT-Keeper for identifying network attacks

| Type               | Accuracy | Recall  | FPR  | f1     |
|--------------------|----------|---------|------|--------|
| Port Scan          | 0.96     | 0.98    | 0.07 | 0.97   |
| Port sweep         | 0.97     | 0.99    | 0.06 | 0.98   |
| Address sweep      | 0.97     | 0.99    | 0.08 | 0.98   |
| Botnet             | 0.99     | 0.99    | 0.02 | 0.99   |
| MitM               | 0.77     | 0.92    | 0.52 | 0.85   |
| Fuzzing            | 0.99     | 0.99    | 0.01 | 0.99   |
| Data theft         | 0.74     | 0.88    | 0.45 | 0.77   |
| Malware injection  | 0.79     | 0.94    | 0.49 | 0.88   |
| SYN flooding       | 0.98     | 0.98    | 0.03 | 0.99   |
| SSL renegotiation  | 0.96     | 0.99    | 0.07 | 0.97   |

6.3. Network Performance

In order to maximize usability, it is vital for network security solutions to have minimal impact on user experience in terms of latency. Therefore, the design of IoT-Keeper is driven by the goal to minimize the latency experienced by end users.

To study the impact on latency while browsing Internet, we studied page load times for top 1000 websites, ranked by Majestic [48]. The measurements were taken for three different scenarios including:

1. IoT-Keeper disabled.
2. IoT-Keeper enabled with 0% cache hit rate.
3. IoT-Keeper enabled with 95% cache hit rate.

We compare the latency experienced when IoT-Keeper is disabled and no analysis is performed to the latency experienced when IoT-Keeper is enabled with anomaly detection and traffic filtering. 0% cache hit rate means that the security policy cache is empty and all traffic flows are analyzed, whereas, 95% cache hit rate means that 95% of network traffic should have a matching policy available in the cache. Section 3 explains how caching reduces the number of requests made to perform anomaly detection, thereby, reducing the latency experienced by user as well as resource consumption.

Figure 7a shows that when IoT-Keeper is enabled, average page load time is increased by upto 4.76% and 15.89% for 95% and 0% cache hit rate respectively. This increase in latency due to anomaly detection is not significantly high, even if there are no cached security policies available at Keeper Gateway. Investigating the increase in page load time for 0% cache hit reveals that the relative increase in page load time is higher (up to 40%) for websites with very small page load times such as, google.com and microsoft.com, but very low ≤ 7% for websites with longer page load time such as, linkedin.com, instagram.com. This is because the page load time for sites such as google.com is very low (≈ 0.5s) and addition of constant time interval (required to perform analysis) will result in a large percentage increase for total page load time. On the other hand, this additional time will account for only a small percentage of time required to load websites with large page load times ≈ 2s, such as, instagram.com, qq.com.

The latency overhead does not depend on the volume of data loaded for webpage, instead it only depends on the time taken to identify traffic type and install flow table entry to handle the traffic. This overhead is only seen for the first time a web page is requested and any future requests for same web page will be handled by the security policy cache, with nearly no delay. Our experiments showed that with 100% cache hit, latency is increased by 1.8% (±1.49%) only.

Identifying the type of traffic flow is the most time consuming task performed by Keeper Gateway. Figure 7b shows the time taken to identify a traffic flow type can account for 13.93% ± (9.55%) percent of the total time required to fetch a web page. In comparison, the time taken for feature extraction, cache lookup and installation of flow table rules is negligible.
IoT-Keeper architecture suggests that Keeper Gateway will serve as a regular gateway used to setup edge networks. Therefore, we study the network performance achieved using Keeper Gateway, in detail. For this purpose, we measured the layer-4, layer-7 goodput, bufferbloat latencies as well as TCP and UDP latencies. Layer-4 goodput was calculated using iperf3 and layer-7 goodput was calculated for bulk file transfer using curl, to include protocol processing overhead as well. Bufferbloat latencies was calculated using netperf with RRUL test (simulated by netperfrunner) and speedtest (simulated using betterspeedtest). These tests use multiple simultaneous connections to simulate heavy network load to study latency and throughput in uplink and downlink. Lastly, TCP and UDP latencies were calculated using qperf.

The experiments were conducted to study the performance for D2D (LAN↔LAN) and D2I (LAN↔WAN) communications. For each type, we compared the performance achieved in insecure setting with IoT-Keeper disabled and secure setting with IoT-Keeper enabled for anomaly detection and traffic filtering.

These results give a qualitative and quantitative understanding of the overheads on network performance due to traffic classification. It is evident that IoT-Keeper does not introduce significant deterioration in network performance in comparison with baseline performance using same hardware.

6.4. System Performance

We investigated the deployment feasibility of IoT-Keeper, using a R-PI, for analyzing network traffic at line speeds. The experimentation was conducted using traffic traces collected for duration of 30 and 60 minutes respectively, from a fully saturated link on R-PI. We calculated the time required to analyze all data points in these samples, using different number of clusters $i$.

Figure 8 shows that the time required to cluster and analyze the data points increases linearly as the number of clusters increase. It can be observed that for $i = 17$, all data points in 30 minutes sample can be analyzed in less than 4 minutes using a R-PI. For comparison, same analysis takes less than 30 seconds on a consumer grade Core i5 laptop with 32Gb memory. Similarly, we can analyze the 60 minute sample, with $i = 50$, in approximately 21 minutes, using R-PI. These results show that IoT-Keeper is able to operate at line speeds using low-cost single board computers.

In order to study the impact of caching over the system performance, we studied how the number of security policies in cache affects the number of classification operations performed. Figure 9a shows that 90% traffic flows in the network can be handled using roughly 200 security policies in the cache. These results validate the hypothesis that most of network traffic from edge networks is destined to only few cloud services. Therefore, a relatively small number of cached security policies can result in high cache hit rate, thereby, lowering the latency, as well as resource footprint.

We analyze our hash-table based implementation of cache to study the performance in terms of lookup time and cache size, relative to the number of cached security policies. As expected, the deep-memory size of cache increases linearly with number of security policies while lookup time remains constant. A few spikes in lookup
time can be attributed to underlying hardware and operating system. Section 3.1 discusses how we can limit the linearly increasing cache size using expiry time and setting an upper bound on the maximum disk space available for cache.

![Graph](image)

(a) Relationship between the number of cached security policies and the number of classification requests made for handling new traffic flows.

![Graph](image)

(b) Behavior of cache lookup time and (deep memory) cache size relative to the number of security policies stored locally.

Figure 9: Effects of cached security policies over system performance

### 7. Related Work

A number of techniques have been proposed to identify anomalies in network traffic [49, 50, 51, 52, 53, 54]. Researchers have studied various feature analysis and machine learning techniques to identify botnets [12, 55, 56], Denial of Service [51] and other attacks in the network [57, 58].

The anomaly detection techniques can be categorized into two types: offline and online. Offline techniques are developed using labeled dataset. Offline algorithms have access to whole dataset and multiple iterations of training and evaluation are performed to produce the final classification model. This exercise consumes lots of time and resources. These algorithms are often used by signature-based network security solutions to identify network attacks.

Online techniques do not have access to complete dataset during model training and they mostly use unlabeled data to perform network traffic classification. They also need to be efficient enough to ensure high detection accuracy at high packet arrival rates, using limited resources.

Majority of existing traffic anomaly detection techniques are developed for offline analysis [49, 12] and require labeled data. Given the number and variety of IoT devices, data collection is challenging. Crowd-sourced data collection has been proposed to address the problem [14] but it has its own limitations [59].

**IoT-Keeper** is an online anomaly detection technique. Therefore, we do not compare its functioning and performance with signature-based network security solutions as these solutions are highly specialized, operate on custom hardware, incur high deployment and operational costs. The performance of signature-based solutions is also limited by the availability of attack signatures.

Among online traffic classification techniques, Securebox was, to the authors’ knowledge, the first one to propose a two tier model, where a lightweight network gateway uses a cloud service to analyze traffic from edge networks [26]. The cloud service supports traffic analysis using software middleboxes, and various machine learning based analysis technique. **IoT-Keeper** addresses the privacy and latency problems in Securebox model by performing traffic analysis locally on the network gateway.

| Metric                      | Direction | Insecure | Secure | Insecure | Secure |
|-----------------------------|-----------|----------|--------|----------|--------|
| Layer 4 goodput             | Up        | 89.97 ±0.77 | 89.69 ±0.03 | 90.11 ±0.80 | 88.91 ±0.10 |
|                             | Down      | 90.46 ±0.34 | 89.70 ±0.02 | 91.01 ±1.53 | 89.70 ±0.15 |
| Layer 7 goodput             | Up        | 87.67 ±1.32 | 84.152 ±0.12 | 89.94 ±0.60 | 86.23 ±0.34 |
| Bufferbloat latency (ms) (Speedtest) | Up        | 2.11 ±0.40 | 3.02 ±0.36 | 3.77 ±0.24 | 3.01 ±0.36 |
| Bufferbloat latency (ms) (RRUL test) | Down      | 90.71 ±2.01 | 92.02 ±2.31 | 81.41 ±2.67 | 82.83 ±2.10 |
| Latency (ms)                | TCP       | 0.37 ±0.004 | 0.42 (±0.003) | 0.38 (±0.003) | 0.38 (±0.004) |
|                             | UDP       | 0.38 (±0.003) | 0.40 (±0.003) | 0.39 (±0.004) | 0.39 (±0.003) |

Table 4: Network performance achieved by IoT-Keeper, in terms of throughput and latency, with R-PI based deployment.
IoT Sentinel [10] identifies the IoT devices by analyzing their network traffic and sets up network access control based on the profile of given IoT device. While IoT Sentinel detects device types with high accuracy, it requires network traces captured during device setup, for this purpose. If a device was already setup, before it was connected to network, IoT Sentinel unable to identify the device and fail to setup network restrictions. Also, the access control policies are coupled with IoT devices and IoT Sentinel does not provide a mechanism to update these policies with the evolution of devices' network behavior. In comparison, IoT-Keeper constantly monitors network activity to detect and block malicious traffic, at any time, irrespective of what device is generating the traffic.

Recently proposed Kitsune [13] uses an ensemble of autoencoders for high accuracy online anomaly detection. Kitsune uses incremental damped statistics to extract features and track devices' network behavior. To reduce memory footprint, Kitsune maintains information about device behavior for a fixed time. Hence, if a device exhibits anomalous behavior long enough, the model will consider it as normal behavior. To address this issue, IoT-Keeper maintains device behavior information through the timeline of its connectivity. This information is used to compare devices' latest behavior to its previous behavior at any point in time. It enables us to detect changes in devices' network behavior due to firmware updates and configuration changes.

DIoT [14] uses the periodicity in IoT device traffic to identify device type and uses device-type-specific anomaly detection model to detect network attacks. Although this technique achieves high accuracy, the anomaly detection model depends on device type identification. Given the huge variety of devices, it is difficult to develop and maintain device-type-specific anomaly model. Meanwhile, any wrong device type identification results will essentially render the device useless, thereby, negatively affecting user experience. DIoT also does not update the anomaly detection model based on changes in device configuration and software updates. Compared to DIoT, IoT-Keeper does not require device-type information to detect anomalies and the anomaly detection scheme can also accommodate any changes in network behavior due to changes in device configuration.

Anomaly detection techniques such as, DIoT, BotMiner [12] mainly detect volumetric attacks (producing large volume of network traffic) such as, Mirai botnet. It is difficult for these techniques to detect attacks such as MitM, ARP Spoofing, which have sporadic network activity similar to normal device activity. IoT-Keeper, on the other hand, is able to detect both these kinds of attacks with high accuracy.

Online detection techniques [10, 13, 14] use the intrinsic device behavior as its normal behavior. Hence, they are unable to detect any anomalies in devices’ network behavior if it is inherently compromised. Meanwhile, IoT-Keeper can capture any discrepancies in a devices’ normal network behavior, during clustering, and labels such behavior as malicious, depending on the feature value distributions observed in given cluster. Therefore, we are able to detect malicious behavior of inherently compromised devices.

Recently proposed anomaly detection techniques also use recurrent neural networks [60, 61, 62, 63] or gated recurrent units [64, 65] for anomaly detection. Some techniques model network traffic as symbols in a language and use a frequency based model to identify anomalous sequence of symbols, indicating network anomalies [61, 14]. These techniques are mainly employed for offline analysis and have high resource footprint.

Any technique which performs remote traffic analysis raise security and privacy concerns for users whose traffic data is analyzed in remote environment. The data storage, processing and analysis in these environments is beyond users’ control and the traffic data being analyzed contains sensitive user data and personally identifiable information. Using IoT-Keeper, we alleviate these concerns by performing traffic analysis within user network, where user has complete ownership and control over the data being analyzed by the network.

Software middleboxes are proposed for on-demand traffic analysis using cloud infrastructure [66]. Middlebox virtualization reduces deployment costs and improves scalability. However, the increase in latency experienced by re-routing traffic through these middleboxes, cost of analyzing huge volumes of network traffic, and privacy implications of analyzing business critical data under third party control, are some of the challenges faced by these proposals.

Various commercial products such as, Cujo9, Dojo10, Core11, Sense12 have been launched to protect IoT and smart homes. These products claim to perform real-time behavioral traffic analysis and deep packet inspection to detect network attacks. At the time of writing, not all of these features are available on latest generation of these devices. Due to limited resources on gateway, most products perform traffic analysis in their respective cloud services, raising aforementioned privacy challenges. Ensuring low latency and high network throughput performance is also a big challenge for these products, which essentially use a proxy to intercept and analyze user traffic flowing through the gateway, impacting the latency and throughput.

Some of these devices claim to perform deep packet inspection on the router itself, resulting in severely degraded network performance. The growing use of encrypted protocols also limits the usefulness of deep packet inspection. Since IoT-Keeper does not perform payload analysis, its performance is not limited by the use of encrypted protocols.

9https://www.getcujo.com/smart-firewall-cujo/
10https://dojo.bullguard.com/
11https://us.norton.com/core
12https://sense.f-secure.com/
8. Discussion

**IoT-Keeper** is a network-based security solution designed to detect anomalies and react to those by isolating the devices exhibiting malicious behavior. Our evaluation demonstrates that the proposed solution efficiently secures edge networks against any attacks. We now discuss possible shortcomings and limitations of IoT-Keeper.

**Feature engineering and model generalization**

Feature engineering is an important step in developing a generalized detection model. The resource limitations of single-board computers required us to identify the least number of features capturing maximum variance in the network traffic data, to detect anomalies. The final feature set had to be compact and generalizable such that it results in consistent anomaly detection performance across multiple datasets. To address these requirements, we analyzyed each feature individually to study its significance for traffic classification. Our analysis revealed that a concise feature set, extracted from network data, can successfully identify anomalies in network traffic. Meanwhile, device logs, if available, can also be helpful in improving the performance of anomaly detection scheme.

It should be noted that IoT-Keeper does not perform deep packet inspection or use any features extracted from unencrypted payload analysis. It can identify malicious network activity of any connected device but cannot detect any malicious data included in packet payload.

**Detecting non-volumetric attacks**

The network activity of volumetric attacks such as denial-of-service attacks, is substantially different from regular device activity because of high traffic volumes and protocols used. We can achieve high accuracy in detecting volumetric attacks, using features extracted from traffic metadata only. However, it is not possible to achieve similar performance, using the same feature set, if the network footprint of an attack is small and infrequent such as, MitM attacks.

Although IoT-Keeper is able to detect these attacks with infrequent network activity, the performance of anomaly detection can be improved by using human expertise to analyze the underlying model. In this regard, Keeper Service can collect various statistics about classification models trained by Keeper Gateway and human experts can analyze this data to identify any discrepancies in the anomaly detection model. Any updates, if needed, are sent from Keeper Service to all gateways deployed in edge networks.

**Free loaders**: By default, IoT-Keeper restricts the network access for malicious devices but it does not fully block their access to the Internet. Although this strategy prevents any attacks in the network, it does not block free loaders from consuming network bandwidth. However, Keeper Gateway allows users to monitor and limit the bandwidth consumed by connected devices, to prevent these free loaders from exhausting limited bandwidth.

**Evolution in device behavior**

The ability of IoT-Keeper to identify device firmware upgrades and configuration changes allows us to limit number of false alarms raised by the system, as well as track the progress of software updates for device deployed in the wild. The knowledge of firmware versions (operated by IoT devices) allows us to readily update security policies, to prevent any attempts to exploit known issues and vulnerabilities in the given firmware version. Given that IoT-Keeper can identify these updates, it does not detect minor upgrades such as, software patches, which do not have significant impact on device’ network behavior.

**Physical tampering with devices**: IoT-Keeper monitors network traffic to detect any malicious activity. Hence, it is not able to detect if a device has any backdoors or is physical tampered with, by an adversary. We assume that any backdoors or physical tampering are motivated by malicious intent to influence devices’ behavior to the favor of adversary. Since majority of IoT devices are connected to the network, any malicious behavior will be detected and blocked by IoT-Keeper.

**Cellular and bluetooth communications**: IoT-Keeper monitors communications passing through Keeper Gateway. Any communications using other channels such as, cellular data, satellite link, can not be secured by the proposed system. The current implementation does not monitor D2D communications occurring via low-power communication protocols. Our study revealed that IoT devices do not generally use low-power protocols for D2D communications and such communications are performed via IoT hub, which can be monitored.

**Attacks against IoT-Keeper**

Our system design limits the attack surface of Keeper Gateway by requiring physical proximity or access to cloud service to perform any configuration changes. In case if an adversary gains access to user credentials for the cloud service configuration portal, it can reset or disable security features on Keeper Gateway and render it useless. To prevent realization of such attacks, IoT-Keeper architecture supports the use of 2-factor authentication, notifications about configuration changes and ability to roll back changes to any point in time using state back-ups.

**MAC address spoofing**: IoT-Keeper sets up network access restrictions based on layer-2 MAC addresses. An adversary can circumvent these restrictions by spoofing device MAC address. In such scenarios, as long as the adversary does not exhibit malicious activity, it will have regular network access but this behavior has no incentive for the adversary. On the contrary, if adversary engages in malicious activity with spoofed MAC address, IoT-Keeper will identify and block that activity.

**Denial of Service**: There is a possibility that adversary can exploit MAC address spoofing to perform DoS attack against Keeper Gateway. In that case, caching will
limit the number of times similar traffic flows, coming from different MAC addresses, are analyzed by the gateway. Moreover, our evaluation also shows that IoT-Keeper is able to perform anomaly detection at line speeds without becoming a bottleneck. An adversary can flood the upstream link in Keeper Gateway but this will block all traffic flows in the network, including attacker’s own traffic, giving no incentive to the attacker.

There is also a possibility of DDoS attacks against Keeper Service. Due to the system architecture, these attacks do not affect Keeper Gateway functionality because it does not depend on Keeper Service. Meanwhile, the attacks against Keeper Service can be handled using several known techniques to prevent DDoS attacks. To prevent Keeper Service from becoming single point of failure when issuing updates, peer-to-peer protocols with checksums and public-key encryption, can be used for transmitting updates to Keeper Gateway deployed in edge networks.

**Adversarial machine learning:** An advanced adversary can use adversarial machine learning techniques [67] to understand the anomaly detection model and generate specially crafted packet flows to circumvent detection mechanism. However, this approach is infeasible because even small changes in packet headers substantially change the network behavior. Meanwhile, payload modifications do not help in circumvention because IoT-Keeper does not perform any payload analysis. Therefore, it is difficult make small enough changes in packet’s header space, which preserve the malicious intent and do not change characteristics of network flow.

**Scalability**

Current architecture uses Keeper Service to only provide support services for Keeper Gateway but system architecture allows us to deploy additional analytics services in the Keeper Service as well. For example, Keeper Gateway can re-route traffic from specific devices through middleboxes and perform sophisticated analysis. In order to speed up model training process, Keeper Gateway can use the resources available in Keeper Service to offload model training. It is also possible to use the computational power of devices connected to the network, such as PC, smartphones, for training anomaly detection model and performing computationally intensive traffic analysis.

9. Conclusion

This paper presents IoT-Keeper, a platform for securing edge networks by detecting malicious network traffic and isolating the devices generating that traffic. IoT-Keeper platform adopts lightweight design and can be deployed using low-cost programmable devices so that traffic classification and security policy enforcement can be performed at the network gateway, in real time. It relies on the feature set extracted from network traffic data, to successfully identify various types of network attacks. The ability to dynamically generate and enforce security policies enables automation of network configuration and readily blocks any malicious actor in the network, using adhoc overlay networks. IoT-Keeper evaluation, using a real world testbed, demonstrates that IoT-Keeper can successfully perform traffic analysis on network gateways, with minimal impact on user experience. Moreover, it does not require sophisticated hardware or modifications on existing IoT and other devices for its operations.

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