A Scalable Platform for Enabling the Forensic Investigation of Exploited IoT Devices and Their Generated Unsolicited Activities

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Introduction

• Internet of Things (IoT) device are widely used in our daily activities
  o Facilitate data collection, monitoring, and information sharing

• Despite their benefits, IoT devices are used as effective attack enablers

• The rise of IoT-driven cyber attacks was marked by the Mirai botnet [1-2]
  o Propagates by exploiting vulnerable IoT devices (e.g., weak/default credentials)
  o Utilizes compromised IoT devices to perform Internet-scale attacks (e.g., DDoS)

• To mitigate such attacks, we need to possess an Internet-scale perspectives of compromised IoT devices and their activities (Challenging)
  o Lack of empirical data on deployed IoT devices
  o Lack of knowledge about their unsolicited behaviors

• Leverage passive network measurements as an alternative approach for inferring and characterizing IoT threats

Background

- Data-driven methodologies for detecting compromised IoT devices [1]
  - Correlating IoT device information and passive network measurements

- IoT device information through active scanning and banner analysis (e.g., Shodan [2])

- Passive network measurements (network telescope or darknet):
  - Traffic captured at unused, yet routable IP addresses
  - Mainly Internet scanning and backscatter traffic (a byproduct of targeted DDoS attacks with spoofed IP addresses)
  - E.g., CAIDA’s darknet (one of the largest existing resources with 16.7M IPs) [3]

IoT (In)Security

Motivated by:
- Insecurity of IoT devices at scale [1]
- Rising number of IoT-tailored malware as a major threat [2-3]

Problem:
- Address the lack of scalable cyber-threat intelligence reporting and analysis capabilities that can trigger informed decisions for in-depth forensic investigations

Approach:
- Leverage data-driven methodologies, passive network measurements, and IoT device information
- Develop a system prototype using a big data analytics framework (Apache Spark [4]) to enable scalable and timely IoT threat detection and analysis

System Architecture and Components

IoT device information collection and traffic filtering
- Collect IoT device information from Shodan [1]
- Filter IoT-generated traffic on the darknet [2]
- IoT-generated traffic is processed as flowtuples

[1] https://www.shodan.io/
System Architecture and Components

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IoT threat repository (ongoing work)
- Collect IoT malware binaries/executables
- Dynamic malware analysis and attribution
System Architecture and Components

IoT traffic analysis (main component)
- Deployed in Apache Spark [1] to support fast and scalable operations
- Data parsing and pre-processing
- Data aggregation (over different time intervals)
- Dynamic device profiling with aggregate flow features
- Multi-stage campaign detection and attribution

Experimental Results

- Collected/Processed data

<table>
<thead>
<tr>
<th>IoT device info</th>
<th>~400K devices (Shodan)</th>
<th>Consumer IoT devices (routers, IP cameras, WAP, etc.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IoT traffic</td>
<td>4TB of darknet data over 5 days</td>
<td>308M packets (flowtuples), mainly TCPSYN (87%)</td>
</tr>
<tr>
<td>Compromised IoT</td>
<td>27,849 devices</td>
<td>~300M scanning packets (97% of all traffic)</td>
</tr>
</tbody>
</table>

- Experimental setup
  - Deployed Apache Spark using PySpark in a standalone mode on a single node
  - Debian Operation System (Ubuntu 18.04 version), 8 CPU cores (Intel® Xeon(R) CPU E3-1240 v5 @ 3.50GHz), 64GB memory

- Present examples of the network forensic capabilities and applications
Monitoring Unsolicited Activities

High level macroscopic views in terms of IoT-generated flows, targeted destination IP addresses, distribution of the packets, targeted destination ports, and total IoT devices

- Overall trends and correlation between the number of generated packets and the targeted IP addresses (reflect Internet scanning activities)
- Highlight increased activities in certain periods (intense scanning campaigns and/or DDoS activities)
- Detecting port scanning activities (e.g., minutes 308, 356, and 366)
Detecting Compromised IoT Devices

Detected about 27K compromised IoT devices that were sending scanning packets (TCP-SYN, UDP, and ICMP-REQ)

- In-depth analysis of the involved IoT devices
- Distribution of scanning packets and compromised devices per protocol
- Intensity of TCP-SYN scans (fewer devices producing significantly larger traffic)
- Distribution of compromised devices per type and hosting countries (may indicate malware outbreak)
Inferring and Monitoring Scanning Campaigns

Identify scanning campaigns by analyzing common scanning objectives (targeted ports)

- The majority of IoT devices scanned a very small list of known ports (e.g., Telnet and HTTP)
- These port sets are associated with known IoT malware (e.g., Mirai)
- UDP/TCP ports comparison in terms of involved IoT devices and the generated scanning traffic
- Presence of targeted ports associated with emerging IoT malware (e.g., port 5555/ADB.Miner)

### Top 10 identified scanning objectives ($S_i$).

<table>
<thead>
<tr>
<th>$S_i$</th>
<th>TCP/UDP Ports</th>
<th>Devices (%)</th>
<th>Packets (M)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>28183, 32124, 37547</td>
<td><strong>932 (6.33)</strong></td>
<td>0.300</td>
</tr>
<tr>
<td>2</td>
<td>445</td>
<td>835 (5.67)</td>
<td>7.687</td>
</tr>
<tr>
<td>3</td>
<td>23, 80, 8080</td>
<td>735 (4.99)</td>
<td>11.200</td>
</tr>
<tr>
<td>4</td>
<td>23, 80, 8080, 37547</td>
<td>403 (2.74)</td>
<td>15.809</td>
</tr>
<tr>
<td>5</td>
<td>28183, 32124</td>
<td>209 (1.42)</td>
<td>0.007</td>
</tr>
<tr>
<td>6</td>
<td>37547</td>
<td>182 (1.24)</td>
<td>0.015</td>
</tr>
<tr>
<td>7</td>
<td>23, 2323</td>
<td><strong>180 (1.22)</strong></td>
<td><strong>16.849</strong></td>
</tr>
<tr>
<td>8</td>
<td>80, 8080</td>
<td>118 (0.80)</td>
<td>1.122</td>
</tr>
<tr>
<td>9</td>
<td>80</td>
<td>100 (0.68)</td>
<td>1.607</td>
</tr>
<tr>
<td>10</td>
<td>80, 443, 8080</td>
<td>89 (0.60)</td>
<td>0.019</td>
</tr>
</tbody>
</table>
Temporal Analysis and Campaign Evolution

- Granular overview of campaign evolution in terms of involved IoT devices and targeted ports
- Campaign dynamics (scanning rate, saturation, involved device types, etc.)
- Infer intensive malware propagation campaigns (e.g., S3 ports 23/80/8080)
Inferring IoT Botnets

Identify correlated devices (possible botnets) within scanning campaigns

- Clustering analysis (DBSCAN) using 16 raw/aggregate flow features
- Detecting botnets of correlated devices with similar behavioral characteristics/features (e.g., 7 clusters within S1 scanning campaign)
- Analysis of devices within botnets may indicate targeted or vulnerable device types/models

<table>
<thead>
<tr>
<th>Clusters</th>
<th>Members</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 (outliers)</td>
<td>60</td>
</tr>
<tr>
<td>1</td>
<td>753</td>
</tr>
<tr>
<td>2</td>
<td>45</td>
</tr>
<tr>
<td>3</td>
<td>53</td>
</tr>
<tr>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
</tr>
</tbody>
</table>

![S1 Clusters (correlated botnets)](image-url)
Identifying DDoS Victims

IoT devices that are targeted by DDoS attacks using spoofed IP addresses, which happen to be within the darknet, generate backscatter replies towards the darknet

- Targeted DDoS attacks (e.g., device #120/Radware firewall located in China and #265/MikroTik router from Iran)
- Hosting countries with the most targeted DDoS victims
- Indication of targeted attacks towards certain device models and/or countries
Performance Evaluation: Execution Times

Evaluation:
- 24 hours data sample (~64M packets)
- Hourly data aggregation/merging

Parse/Aggregate:
- Relatively short time (mean<50s)
- Linear correlation between execution times and the processed flows (<2 minutes for processing 3.8M flottuples)

Device profiling (merge):
- Requires the longest time (exponential increase with cumulative number of devices)
- Less than 59 minutes to perform aggregation and device profiling for a full day (~17K Devices)
- Can be reduced with a multi-cluster implementation
Memory/CPU Usage

Reasonable Memory/CPU usage
- Scalable operations with less than 10 GB of required memory
- Experience extended periods of CPU intensive operations with cumulative IoT devices/traffic, which can be reduced through a multi-cluster implementation

Heap Usage

CPU Usage

Memory/CPU usage during the first four intervals T1-T4 (hours)
Main Takeaways

• Proposed and evaluated an effective and scalable system prototype for IoT-centric cyber forensic investigations by leveraging
  o Big data analytics frameworks such as Apache Spark
  o Data-driven methodologies using passive network traffic and IoT device information

• Addressed main operational challenges such as process automation, scalability, and fast operations

• Demonstrated the capabilities of the system as an infrastructure for enabling cyber-forensic investigations

• Leveraged empirical data to examine the effectiveness of the system and evaluate its performance with traffic generated by compromised IoT devices in the wild
Thank you

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