Machine Learning DDoS Detection for Consumer Internet of Things Devices

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***Abstract*—An increasing number of Internet of Things (IoT) devices are connecting to the Internet, yet many of these devices are fundamentally insecure, exposing the Internet to a variety of attacks. Botnets such as Mirai have used insecure consumer IoT devices to conduct distributed denial of service (DDoS) attacks on critical Internet infrastructure. This motivates the development of new techniques to automatically detect consumer IoT attack traffic. In this paper, we demonstrate that using IoT-specific network behaviors (e.g., limited number of endpoints and regular time intervals between packets) to inform feature selection can result in high accuracy DDoS detection in IoT network traffic with a variety of machine learning algorithms, including neural networks. These results indicate that home gateway routers or other network middleboxes could automatically detect local IoT device sources of DDoS attacks using low-cost machine learning algorithms and traffic data that is flow-based and protocol-agnostic.**

***Keywords*-Internet of Things; Anomaly Detection; DDoS; Machine Learning; Feature Engineering**

I. Introduction

The number of Internet of Things (IoT) devices is projected to grow from 8 billion in 2017 to 20 billion in 2020 [1]. Yet, many of these IoT devices are fundamentally insecure. One analysis of 10 currently popular IoT devices found 250 vulnerabilities, including open telnet ports, outdated Linux firmware, and unencrypted transmission of sensitive data [2], [3].

The proliferation of insecure IoT devices has resulted in a surge of IoT botnet attacks on Internet infrastructure. In October 2016, the Mirai botnet commanded 100,000 IoT devices (primarily CCTV cameras) to conduct a distributed denial of service (DDoS) attack against Dyn DNS infrastructure [4]. Many popular websites, including Github, Amazon, Netflix, Twitter, CNN, and Paypal, were rendered inaccessible for several hours. In January 2017, the Mirai source code was publicly released; DDoS attacks using Mirai-derived IoT botnets have since increased in frequency and severity [5].

This growing threat motivates the development of new techniques to identify and block attack traffic from IoT botnets. Recent anomaly detection research has shown the promise of machine learning (ML) for identifying malicious Internet traffic [6]. Yet, little effort has been made to engineer ML models with features specifically geared towards IoT device networks or IoT attack traffic. Fortunately, however, IoT traffic is often distinct from that of other Internet connected devices (e.g. laptops and smart phones) [7]. For example, IoT devices often communicate with a small finite set of endpoints rather than a large variety of web servers. IoT devices are also more likely to have repetitive network traffic patterns, such as regular network pings with small packets at fixed time intervals for logging purposes.

Building on this observation, we develop a machine learning pipeline that performs data collection, feature extraction, and binary classification for IoT traffic DDoS detection. The features are designed to capitalize on IoT-specific network behaviors, while also leveraging network flow characteristics such as packet length, inter-packet intervals, and protocol. We compare a variety of classifiers for attack detection, including random forests, K-nearest neighbors, support vector machines, decision trees, and neural networks.

Given the lack of public datasets of consumer IoT attack traffic, we generate classifier training data by simulating a consumer IoT device network. We set up a local network comprised of a router, some popular consumer IoT devices for benign traffic, and some adversarial devices performing DoS attacks. Our classifiers successfully identify attack traffic with an accuracy higher than 0.999. We found that random forest, K-nearest neighbors, and neural net classifiers were particularly effective. We expect that deep learning classifiers will continue to be effective with additional data from real-world deployments.

Our pipeline is designed to operate on network middleboxes (e.g. routers, firewalls, or network switches) to identify anomalous traffic and corresponding devices that may be part of an ongoing botnet. The pipeline is flow-based, stateless, and protocol-agnostic; therefore, it is well suited for deployment on consumer home gateway routers or ISP-controlled switches. To our knowledge, this is the first network anomaly detection framework to focus on IoT-specific features, as well as the first to apply anomaly detection specifically to IoT botnets at the local network level.

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II. Background and Related Work

In this section, we present a brief background on network anomaly detection and middlebox limitations.

A. Network Anomaly Detection

Anomaly detection aims to identify patterns in data that do not conform to expected behavior. In the context of our work, anomaly detection techniques may be used to discern attack traffic from regular traffic. Simple threshold-based techniques are prone to incorrectly classifying normal traffic as anomalous traffic and are unable to adapt to the evolving nature of attacks [6]. More sophisticated anomaly detection algorithms, particularly those using machine learning, can help minimize false positives. Such approaches include deep neural networks, which promise to outperform traditional machine learning techniques for sufficiently large datasets.

Anomaly detection has long been used in network intrusion detection systems (NIDS) for detecting unwanted behavior in non-IoT networks. The NIDS literature can therefore inform the choice of anomaly detection methods for IoT networks. In particular, the literature suggests nearest neighbor classifiers [8], support vector machines [9], and rule-based schemes like decision trees and random forests [10], [11] as promising approaches.

Although there are parallels between NIDS and IoT botnet detection, there has been little work tailoring anomaly detection specifically for IoT networks. Our underlying hypothesis is that IoT traffic is different from other types of network behavior. For example, while laptops and smart phones access a large number of web endpoints due to web browsing activity, IoT devices tend to send automated pings to a finite number of endpoints. IoT devices also tend to have a fixed number of states, so their network activity is more predictable and structured. For instance, a smart light bulb could have three states: "On," "Off", and "Connecting to Wi-Fi," each with distinctive network traffic patterns.

This hypothesis is supported by the literature. Apthorpe et al. demonstrate how the finite states of consumer IoT devices can actually be reflected in the repeated temporal structures of send/receive traffic rates; this can even be used to infer consumer usage behaviors [7]. Similarly, the SCADA anomaly detection literature notes the unique network traffic patterns of sensors and controllers in infrastructure systems [12], [13]. Miettinen et al. further show how machine learning techniques can leverage the unique patterns of IoT network traffic for similar tasks, such as device identification [14]. Therefore, we use network traffic features that capture IoT-specific behaviors to better model IoT DoS attack traffic for anomaly detection.

B. Network Middlebox Limitations

Network middleboxes have limited memory and processing power, imposing constraints on the algorithmic techniques used for anomaly detection. The literature contains suggestions for how to meet these constraints. For example, Sivanathan et al. investigated the use of software defined networks to monitor network traffic at flow-level granularity [15]. Their work suggests that using flow-based features can be effective in detecting security threats without incurring the high cost of deep-packet inspection. An anomaly detection framework for a consumer smart home gateway router should therefore have the following characteristics:

- *Lightweight Features*. Routers must handle high bandwidth traffic, so any features generated must be lightweight [16]. In order for an algorithm to scale to high bandwidth application, a given algorithm must rely on network flow statistics (how packets are sent) as opposed to deep packet inspection (what is in a packet).
- *Protocol Agnostic Features*. Routers must process packets from a variety of protocols (e.g. TCP, UDP, HTTP, etc.), so the algorithm must consider packet features shared by all protocols.
- *Low Memory Implementation*. Routers are only able to maintain limited state due to memory constraints; caching adds latency and complexity. Thus, an optimal algorithm is either stateless or requires storing flow information over short time windows only [15].

III. Threat Model

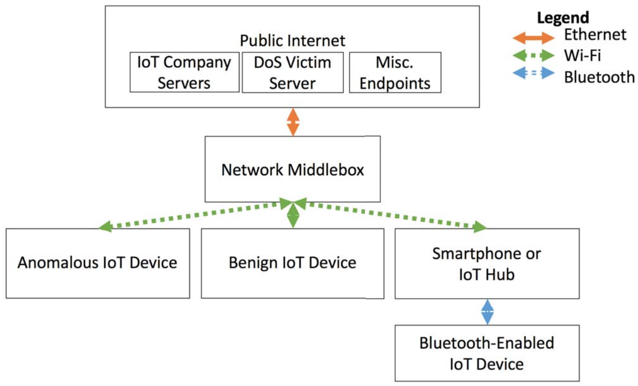
Our threat model (Fig. 1a) makes various assumptions about consumer IoT networks. We assume the network includes an on-path device, such as a home gateway router or other middlebox, that can observe traffic between consumer IoT devices on the local network (e.g. a smart home LAN) and the rest of the Internet. The device at this observation point can inspect, store, manipulate, and block any network traffic that crosses its path. All traffic between WiFi devices on the LAN or from devices to the Internet traverses this middlebox.

Our goal is to detect and prevent DoS attack traffic originating from devices within the smart home LAN. The DoS victim may be another device on the LAN or elsewhere on the Internet. Any device connected to the middlebox can send both network and attack traffic within the same time period. Each device is also capable of conducting a variety of different DoS attacks in series, and successive attacks can vary in duration. This reflects how a remote botnet command and control (C&C) may change orders. We assume that the time range of DoS attacks are roughly 1.5 minutes, a common duration for DoS attacks attempting to avoid detection [5].

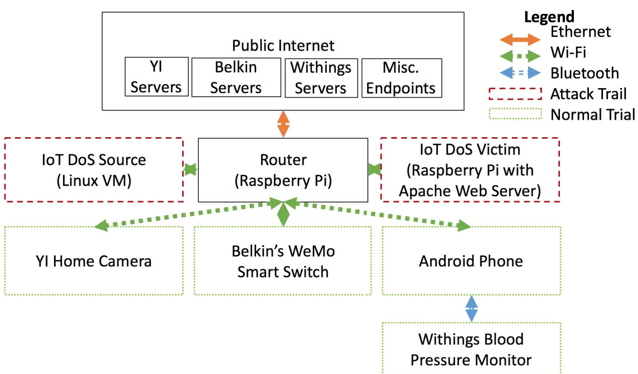
IV. Anomaly Detection Pipeline

In this section, we present a machine learning DDoS detection framework for IoT network traffic. Our anomaly detection pipeline has four steps (Fig. 2):

1) *Traffic Capture.* The traffic capture process records the source IP address, source port, destination IP address,



(a) Threat model



(b) Experiment setup

Figure 1: Consumer IoT network threat model and corresponding experiment setup for collecting normal and DoS attack traffic training data.

destination port, packet size, and timestamp of all IP packets sent from smart home devices.

2) *Grouping of Packets by Device and Time.* Packets from each IoT device are separated by source IP address. Packets from each device are further divided into non-overlapping time windows by timestamps recorded at the middlebox.
3) *Feature Extraction.* Stateless and stateful features are generated for each packet based on domain knowledge of IoT device behavior. The stateless features are predominantly packet header fields, while the stateful features are aggregate flow information over very short time windows, requiring limited memory to support on-router deployment. (Section IV-B).
4) *Binary Classification.* K-nearest neighbors, random forests, decision trees, support vector machines, and deep neural networks can differentiate normal traffic from DoS attack traffic with high accuracy (Section V-A).

A. Traffic Collection

We set up a experimental consumer IoT device network to collect realistic benign and malicious IoT device traffic (Fig. 1b). We configured a Raspberry Pi v3 as a WiFi access point to act as a middlebox. We then connected a YI Home Camera [17] and Belkin WeMo Smart Switch [18] to the Raspberry Pi's WiFi network. A Withings Blood Pressure Monitor was also connected by Bluetooth to an Android smartphone associated with the WiFi network [19].

To collect normal (non-DoS) traffic, we interacted with all three IoT devices for 10 minutes and recorded `pcap` files, logging all packets sent during that time period. We performed many interactions that would occur during regular device use, including streaming video from the YI camera to the server in HD and RD modes, turning the WeMo Smart Switch on/off and installing firmware updates, collecting blood pressure measurements from the Withing's Blood Pressure monitor, and sending the measurements to a cloud server for storage. We then filtered out all non-IoT traffic from the `pcap` recordings, including background traffic from the Android phone.

Collecting DoS traffic was more challenging. To avoid the security risks and complexity of running the real Mirai botnet code, we simulated the three most common classes of DoS attacks a Mirai-infected device will run: a TCP SYN flood, a UDP flood, and a HTTP GET flood [5]. We used a Kali Linux virtual machine running on a laptop as the DoS source, and a Raspberry Pi 2 running an Apache Web Server as the DoS victim. We connected both devices via WiFi to our Raspberry Pi 3 access point. The DoS source then targeted the victim's IP address with each class of DoS attack for approximately 1.5 minutes each. The access point recorded PCAPs of the attack traffic using the Linux dumpcap tool. The HTTP GET Flood was simulated using the Goldeneye tool [20]. The TCP SYN Flood and UDP Flood were simulated using Kali Linux's hping3 utility [21].

We then combined the DoS traffic with the normal traffic, spoofing source IP addresses, MAC addresses, and packet send times to make it appear as if the IoT devices simultaneously produced normal traffic and conducted DoS attacks. Each of the three IoT-devices appeared to execute each of the three DoS attack classes once within a 10 minute internal. The attacks occurred in a random order for a random duration ranging uniformly from 90 to 110 seconds each. Thus, we collected roughly 300 seconds (5 minutes) of attack traffic per device. The distribution of attacks between devices was independent.

This process produced a dataset of 491,855 packets, comprised of 459,565 malicious packets and 32,290 benign packets.

B. Feature Engineering

We explore two classes of features and analyze why they are relevant to differentiating normal and attack IoT traffic. *Stateless features* can be derived from flow-independent characteristics of individual packets. These features are generated without splitting the incoming traffic stream by

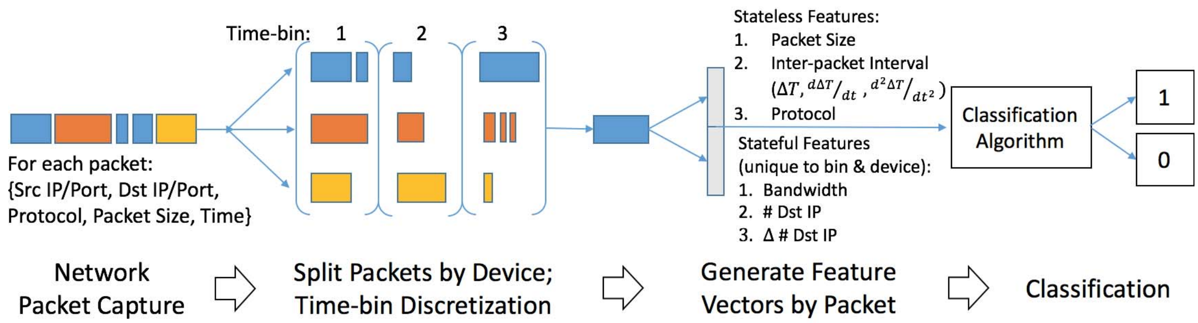


Figure 2: IoT DDoS detection pipeline.

IP source. Thus, these features are the most lightweight. *Stateful features* capture how network traffic evolves over time. There is inherent overhead in generating these features, as we split the network traffic into streams by device and divide the per-device streams into time windows. The time windows serve as a simple time-series representation of the devices' evolving network behavior. These features require aggregating statistics over multiple packets in a time window; the middlebox performing classification must retain state, but the amount of state can be limited by using short (e.g. 10-second) time windows.

1) Stateless Features:

Packet Size: The distribution of packet sizes differs significantly between attack and normal traffic (Fig. 3a). Over 90% of attack packets are under 100 bytes, while normal packets vary between 100 and 1,200 bytes. A device conducting a DoS attack, such as a TCP SYN Flood, is trying to open as many connection request as possible with the victim to exhaust the victim server's resources. Thus, an attacker wants to keep the size of the packets as small as possible in order to maximize the number of connection requests per second. In comparison, normal traffic can range from simple server pings indicating that the device is active (small packets) to video streaming data (large packets).

Inter-packet Interval: Normal IoT traffic has limited burstiness (Fig. 3b-d). Most packets are sent at regular intervals with appreciable time between packets. This may reflect IoT network pings or other automated network activities. In contrast, a vast majority of DoS attack traffic has close to zero inter-packet intervals (ΔT) and high first and second derivatives of inter-packet intervals. Using ΔT, $\frac{d\Delta T}{dt}$, and $\frac{d^2\Delta T}{dt^2}$ as features allows a classifier to capitalize on this difference between normal and DoS traffic.

Protocol: Normal and DoS attack traffic also have varying protocol distributions (Fig. 3e-f). UDP packets outnumber TCP packets in normal traffic by almost a factor of three due to UDP video streaming. In comparison, TCP packets outnumber UDP packets in attack trafic by almost the same ratio. Attack traffic also includes fewer protocols in total. We capture protocol differences in a feature with a one-hot encoding of the three most popular attack protocols (IS_TCP, IS_UDP, and IS_HTTP) and another binary indicator to reflect all other types of protocols (IS_OTHER). This captures the most popular protocols while minimizing noise and unnecessary dimensionality associated with less relevant protocols.

2) Stateful Features:

Bandwidth: The literature contains evidence that bandwidth usage can be used to characterize network traffic patterns of IoT devices. For example, Apthorpe et al. were able to characterize consumer IoT device usage patterns from send/receive rates, but dividing network traffic by source device was necessary for the analysis [7]. Similarly, our pipeline splits network traffic by source device and calculates the average bandwidth within 10-second time windows to measure the instantaneous bandwidth associated with each device. There are minor distributional differences in bandwidth usage between the normal and attack traffic (Fig. 3g). We predict that a ML model will be able to leverage these differences.

IP Destination Address Cardinality and Novelty: IoT devices are characterized by the limited number of endpoints with which they communicate [7]. For example, a WeMo smart switch communicates with only four endpoints for the purposes of activation/deactivation from the cloud, retrieving firmware updates, and logging its status. Another key characteristic of IoT device traffic is that the set of destination IP addresses rarely changes over time.

We craft two features to reflect this behavior. First, a count of distinct destination IP addresses within a 10-second window; more endpoints may indicate attack traffic. Second, we calculate the change in the number of distinct destination IP addresses between time windows; new endpoints might suggest that the device is conducting an attack. Fig. 3h supports the importance of these two features. Packets associated with attack traffic are in contact with, on average, more endpoints. This minor distributional difference can be leveraged in differentiating normal and attack traffic.

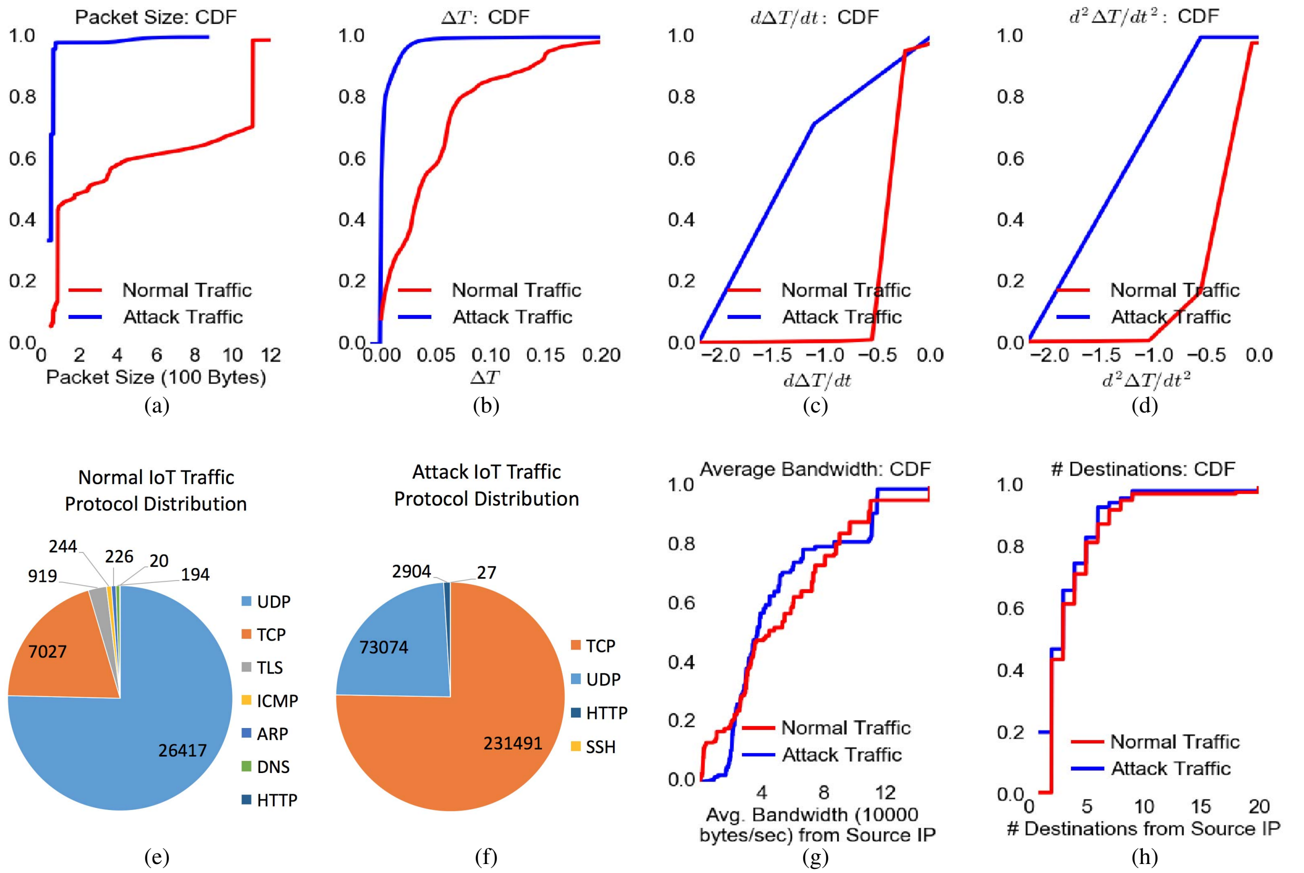


Figure 3: Comparison of feature statistics for normal versus DoS attack traffic. *a)* Packet sizes. *b–d)* Inter-packet intervals (ΔT), $d\Delta T/dt$, and $d^2\Delta T/dt^2$. *e–f)* Protocol distributions. *g)* Average bandwidth over 10 second time windows. *h)* Number of unique IP destinations in 10 second time windows.

V. Results

A. Classification

We tested five machine learning algorithms to distinguish normal IoT packets from DoS attack packets:

1) K-nearest neighbors "KDTree" algorithm (KN)
2) Support vector machine with linear kernel (LSVM)
3) Decision tree using Gini impurity scores (DT)
4) Random Forest using Gini impurity scores (RF)
5) Neural Network (NN): 4-layer fully-connected feed-forward neural network (11 neurons per layer), trained for 100 epochs with batch size 32 using binary cross-entropy loss; hyperpameters chosen by optimization on a validation set

We implemented these machine learning models using the Scikit-learn Python library [22], except for the neural network, which was implemented using the Keras library [23]. All hyper-parameters were the default values unless otherwise noted.

We trained the classifier on a training set with 85% of the combined normal and DoS traffic and calculated classification accuracy on a test set of the remaining traffic (Table I). The accuracies of our four classifiers ranged from approximately 0.91 to 0.99. Note that there are almost 15 times as many attack packets as there are normal packets due to the flooding nature of the DoS attacks. Thus, a naive baseline prediction algorithm that predicts that all packets are malicious would achieve a baseline accuracy of 0.93.

Table I: IoT Traffic Classification Results

	KN	**LSVM**	**DT**	**RF**	**NN**
Precision (Normal)	.998	.992	.996	.999	.983
Precision (Attack)	.999	.991	.999	.999	.999
Recall (Normal)	.993	.870	.993	.998	.989
Recall (Attack)	.999	.999	.999	.999	.998
F1 (Normal)	.995	.927	.994	.998	.986
F1 (Attack)	.999	.995	.996	.999	.999
Accuracy	.999	.991	.999	.999	.999

The linear SVM classifier performed the worst, suggesting that the data is not linearly separable. The decision tree classifier performed well, achieving an accuracy of 0.99, suggesting that the data can be segmented in a higher feature space. The K-nearest neighbors classifier also achieved the same accuracy, suggesting that the two different data

Table II: Feature Importance using Gini Impurity Scores.

Feature	Gini Score
Packet Size	.510
is_HTTP	.177
ΔT	.070
is_TCP	.068
is_OTHER	.043
is_UDP	.041
$d\Delta T/dt$	.018
$d^2\Delta T/dt^2$	.012
Bandwidth	.006
# Destinations	.004
Δ # Destinations	.003

Table III: Classifier performance, with and without IoT-specific stateful (temporal) features.

F1 (Normal)	KN	LSVM	DT	RF	NN
Stateless Features	.967	.920	.977	.981	.939
All Features	.995	.921	.995	.998	.989

classes clustered well in feature-space. The neural network performed surprisingly well despite having fewer than half a million training samples from a 10-minute packet capture. Given the nature of the algorithm, the neural network is expected to scale its performance with the amount of available training data.

B. Feature Importance

The stateless features greatly outperformed the stateful features, as indicated by Gini impurity score (Table II). We expected this result, since the differences in the cumulative distributions of normal and attack traffic were more pronounced than those of the stateless features (Fig. 3). This result suggests that real-time anomaly detection of IoT attack traffic may be practical because the stateless features are lightweight and derived from network-flow attributes (e.g. 5-tuple and packet size).

Incorporating stateful features nonetheless improved accuracy compared to classification with the stateless features alone (Table III). All of the classifiers experienced a 0.01 to 0.05 increase in F1 score by including stateful features. This demonstrates that applying domain knowledge about IoT device behaviors to feature engineering can enhance DoS detection performance.

VI. Discussion & Future Work

This preliminary work demonstrates that simple classification algorithms and low-dimensional features can effectively distinguish normal IoT device traffic from DoS attack traffic. This result motivates follow-up research to evaluate IoT DoS detection in more real-world settings.

First, we would like to replicate the results of this study with normal traffic from additional IoT devices and with attack traffic recorded from a real DDoS attack. This could involve using published code to create an IoT device botnet on a protected laboratory network or collaborating with an ISP to obtain NetFlow records or packet captures recorded during a DDoS attack. This will be an essential test of the method's external validity.

Collecting a larger dataset would also allow us to see how DoS detection accuracy is affected by the amount and diversity of IoT traffic. The network behavior of IoT devices varies widely by device type [7]. We are curious whether certain types of devices are more amenable to network anomaly detection, perhaps because their normal traffic follows more regular patterns, or vice versa.

We would also like to experiment with additional features and more complex machine learning techniques beyond those discussed in this paper. We believe that there is great potential for the application of deep learning to anomaly detection in IoT networks, especially for detecting attacks that are more subtle than DoS floods. We hope that this work inspires further efforts to develop network protection techniques specifically designed for IoT devices.

It is also an open question how best to intervene once an IoT device is discovered to be part of a DDoS attack. Simply cutting the device off from the network might not be feasible, especially if the device is essential (e.g. a blood sugar monitor or a home water pump), because many smart devices do not retain basic functionality without network connectivity [24]. Notifying the user is an option, but many users of home IoT devices will be unequipped to perform device maintenance beyond powering off or disconnecting the device.

VII. Conclusion

In this work, we showed that packet-level machine learning DoS detection can accurately distinguish normal and DoS attack traffic from consumer IoT devices. We used a limited feature set to restrict computational overhead, important for real-time classifcation and middlebox deployment. Our choice of features was based on the hypothesis that network traffic patterns from consumer IoT devices differ from those of well-studied non-IoT networked devices. We tested five different ML classifiers on a dataset of normal and DoS attack traffic collected from an experimental consumer IoT device network. All five algorithms had a test set accuracy higher than 0.99. These preliminary results motivate additional research into machine learning anomaly detection to protect networks from insecure IoT devices.

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REFERENCES

[1] (2016) Unlocking the potential of the internet of things. McKinsey & Company. [Online]. Available: http://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/the-internet-of-things-the-value-of-digitizing-the-physical-world

[2] (2015) Internet of things research study. Hewlett Packard Enterprise. [Online]. Available: http://h20195.www2.hpe.com/V4/getpdf.aspx/4aa5-4759enw

[3] (2016) Internet of things (iot) security and privacy recommendations. BITAG. [Online]. Available: https://www.bitag.org/report-internet-of-things-security-privacy-recommendations.php

[4] S. Hilton. (2016) Dyn analysis summary of friday october 21 attack. Dyn. [Online]. Available: https://dyn.com/blog/dyn-analysis-summary-of-friday-october-21-attack/

[5] (2016) Threat advisory: Mirai botnet. Akamai. [Online]. Available: https://www.akamai.com/us/en/multimedia/documents/state-of-the-internet/akamai-mirai-botnet-threat-advisory.pdf

[6] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," *ACM computing surveys (CSUR)*, vol. 41.3: 15, 2009.

[7] N. Apthorpe, D. Reisman, and N. Feamster, "A smart home is no castle: Privacy vulnerabilities of encrypted iot traffic," 2016.

[8] L. Ertoz, E. Eilertson, A. Lazarevic, P.-N. Tan, V. Kumar, J. Srivastava, and P. Dokas, "Minds minnesota intrusion detection system," *In Data Mining: Next Generation Challenges and Future Directions*, 2004.

[9] E. Eskin, W. Lee, and W. Stolfo, "Modeling system call for intrusion detection using dynamic window sizes," 2001.

[10] M. Qin and K. Hwang, "Frequent episode rules for internet anomaly detection," 2004.

[11] D. Barbard, J. Couto, S. Jajodia, and N. Wu, "Adam: A testbed for exploring the use of data mining in intrusion detection," *SIGMOD*, vol. 30:4, 2001.

[12] J. Bigham, D. Gamez, and N. Lu, "Safeguarding scada systems with anomaly detection," in *Computer Network Security*, V. Gorodetsky, L. Popyack, and V. Skormin, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 171–182.

[13] S. N. Shirazi, A. Gouglidis, K. N. Syeda, S. Simpson, A. Mauthe, I. M. Stephanakis, and D. Hutchison, "Evaluation of anomaly detection techniques for scada communication resilience," in *2016 Resilience Week (RWS)*, Aug 2016, pp. 140–145.

[14] M. Miettinen, S. Marchal, I. Hafeez, N. Asokan, A. Sadeghi, and S. Tarkoma, "Iot sentinel: Automated device-type identification for security enforcement in iot," *CoRR*, vol. abs/1611.04880, 2016. [Online]. Available: http://arxiv.org/abs/1611.04880

[15] A. Sivanathan, D. Sherratt, H. H. Gharakheili, and A. V. Vijay Sivaraman, "Low-cost flow-based security solutions for smart-home iot devices," 2016.

[16] S. Hao, N. A. Syed, N. Feamster, A. G. Gray, and S. Krasser, "Detecting spammers with snare: Spatio-temporal network-level automatic reputation engine," *USENIX security symposium*, vol. 9, 2000.

[17] (2017) Yi home camera. [Online]. Available: https://www.yitechnology.com/yi-home-camera

[18] (2017) Wemo insight smart plug. [Online]. Available: http://www.belkin.com/us/F7C029-Belkin/p/P-F7C029/

[19] (2017) Wireless blood pressure monitor. [Online]. Available: https://health.nokia.com/us/en/blood-pressure-monitor

[20] (2017) Goldeneye code repository. [Online]. Available: https://github.com/jseidl/GoldenEye

[21] (2017) hping3 package description. [Online]. Available: http://tools.kali.org/information-gathering/hping3

[22] (2017) Scikit learn: Machine learning in python. [Online]. Available: http://scikit-learn.org/stable/

[23] F. Chollet *et al.*, "Keras," https://github.com/fchollet/keras, 2015.

[24] N. Apthorpe, D. Reisman, and N. Feamster, "Closing the blinds: Four strategies for protecting smart home privacy from network observers," *Workshop on Technology and Consumer Protection (ConPro)*, 2017.