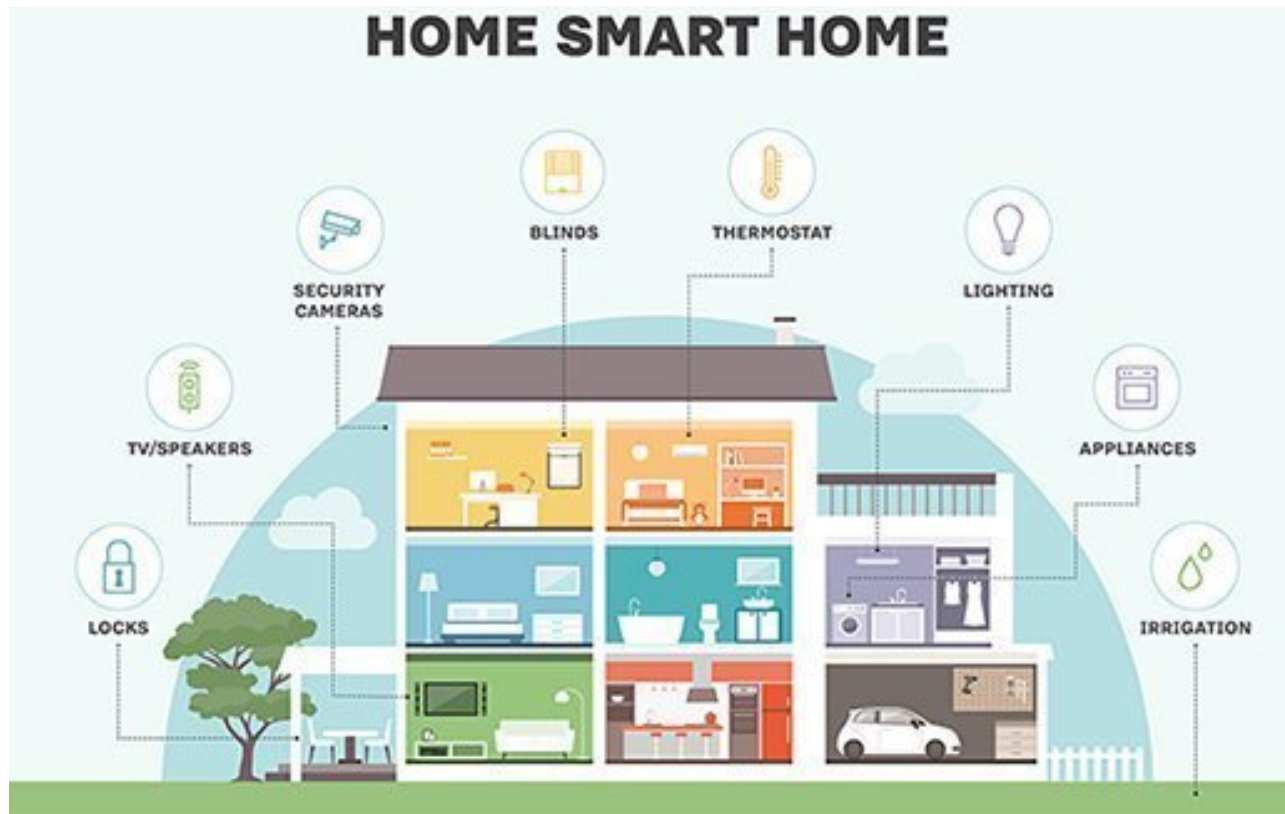


Securing Smart Homes via Software-Defined Networking and Low-Cost Traffic Classification

**Authors: Holden Gordon, Christopher Batula,
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Liu**

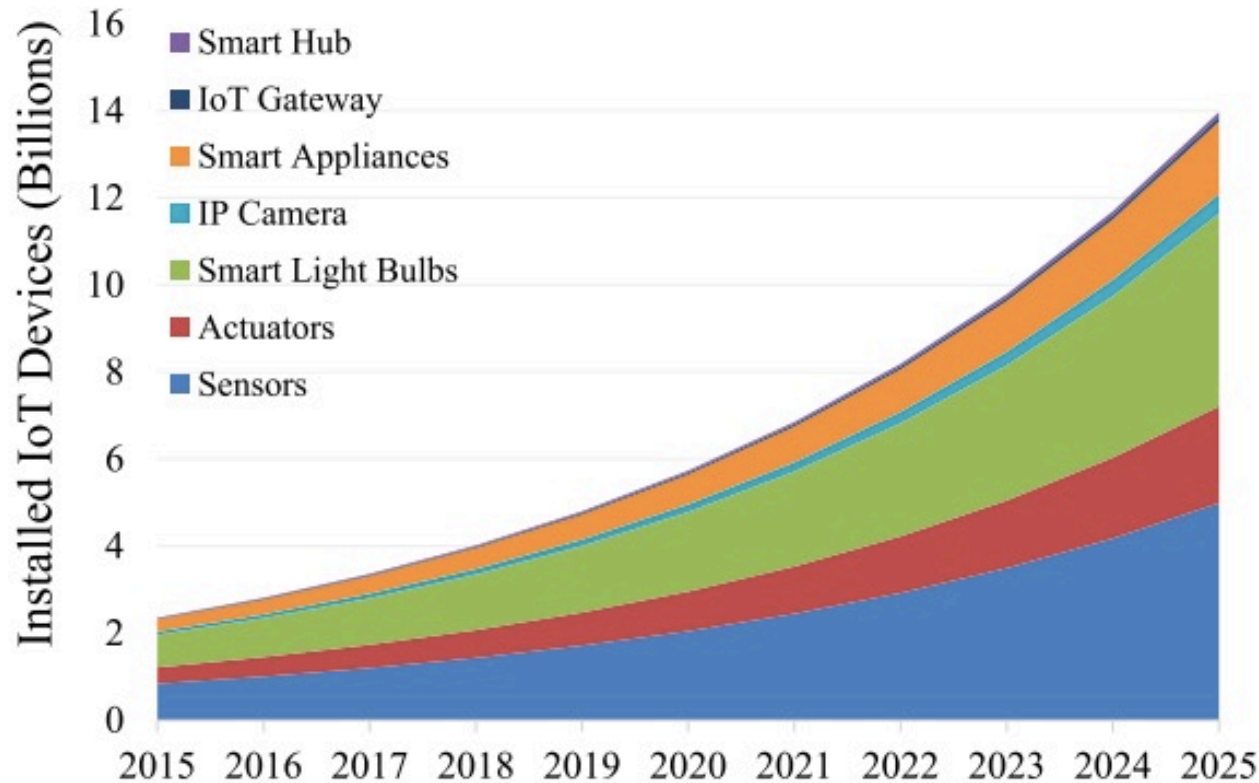
COMPSAC July 2021

- Smart home and smart home security
- Proposed testing environment
- Proposed features
- Result and discussions

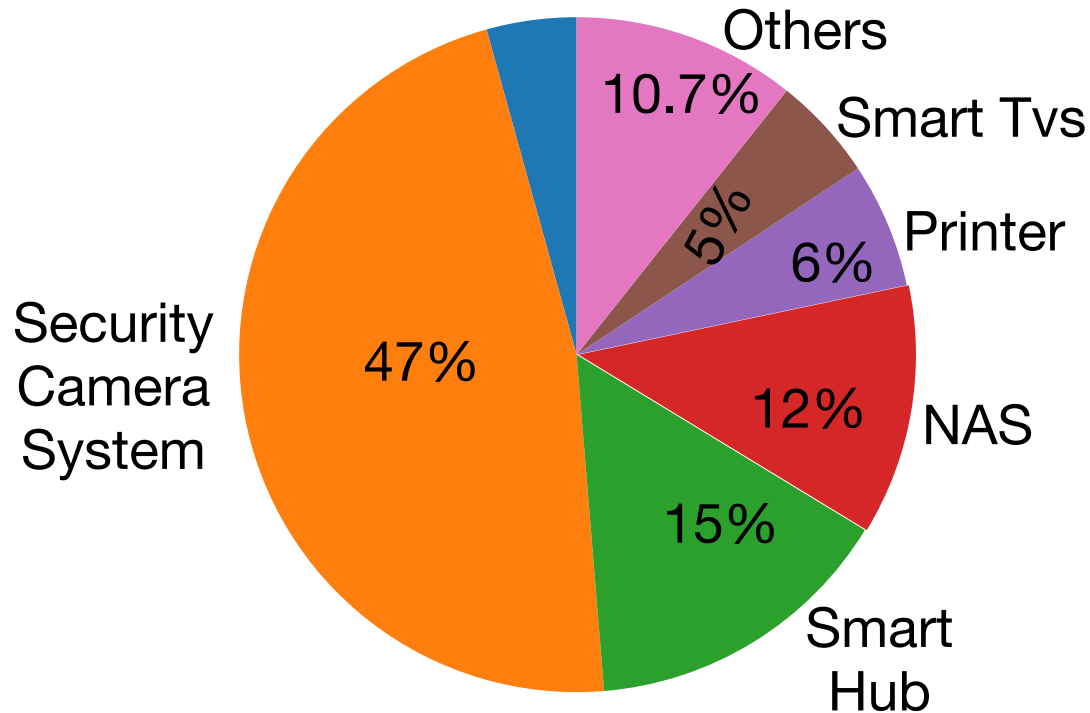


- Smart homes — house with wired and wireless interconnected devices.
- Provide services — voice assistants, security cameras etc.

Smart Home IoT devices growth



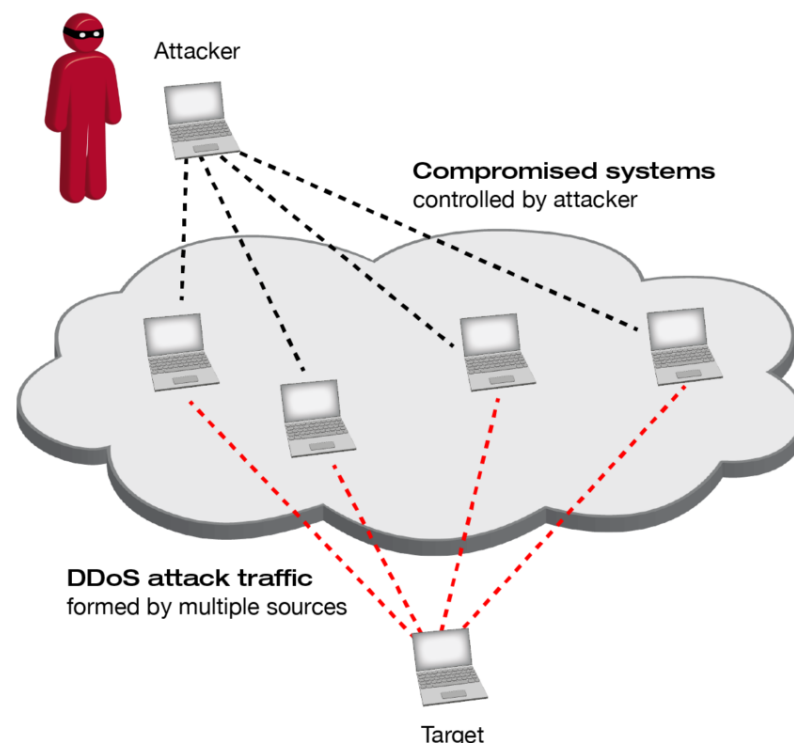
The number of interconnected smart home devices will reach 72 billion (approx) by 2025.



IoT Devices — attractive to hackers.

Attacks on Smart Home Devices

- IoT devices are vulnerable to various attacks:
 - *distributed Denial of Service attacks (DDoS)*,
 - network scan attacks,
 - SQL injections,
 - zero-day attack and,
 - ransomware attacks
- Reasons:
 - heterogeneity of IoT devices.
 - low storage and computation resources.
 - generate massive data.



- DDoS attacks — target service disruption.
- DDoS attacks — disconnects IoT devices from Access Point.

Software-Defined Networking

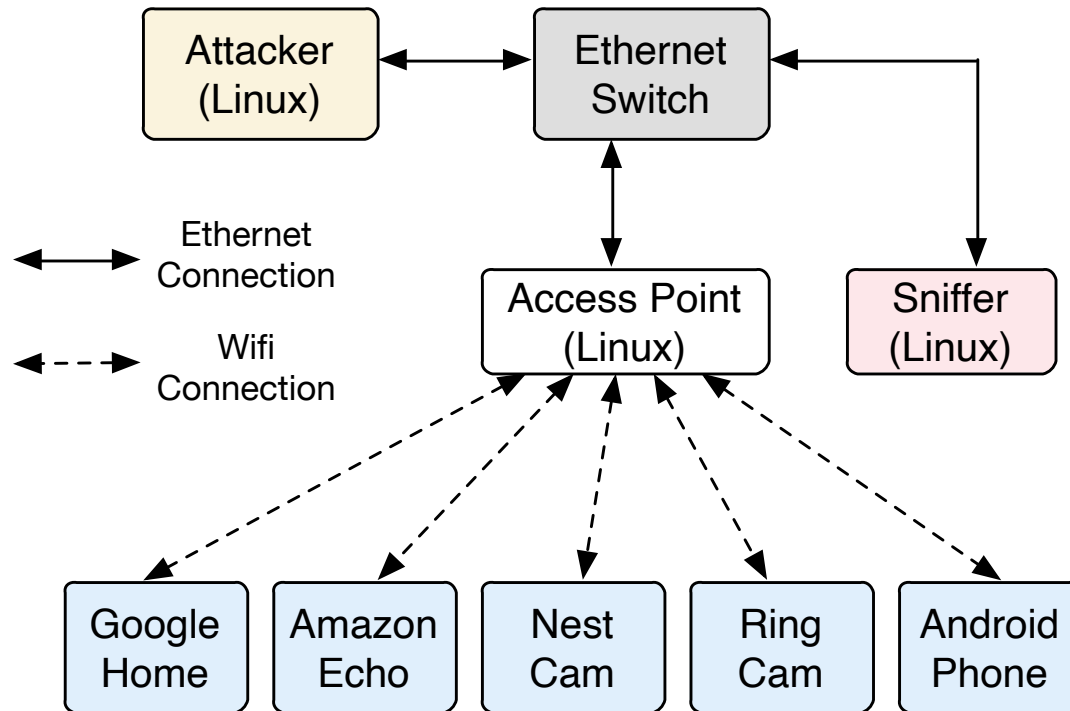
- Traditional system inadequate. Why?
 - high volume of data.
 - large amount of connected IoT devices.
- Solution — Software-Defined Networking (SDN):
 - centralize network management,
 - provide flow-based statistics,
 - helps developing flexible solutions.
- SDN and Machine Learning —
 - helps intelligent decisions making.
 - Enhance smart home security via — IoT device classification and DDoS detection.

- *Our work focus on SDN based low cost IoT device classification and DDoS detection.*

Contribution —

- novel SDN-based architecture using GNS3 network simulator.
- deployable on low-cost edge system.
- minimum set of flow-based features for both device classification and DDoS detection.
- utilize non-cumulative statistics to reduce controller and switch communication overhead.

Smart Home network



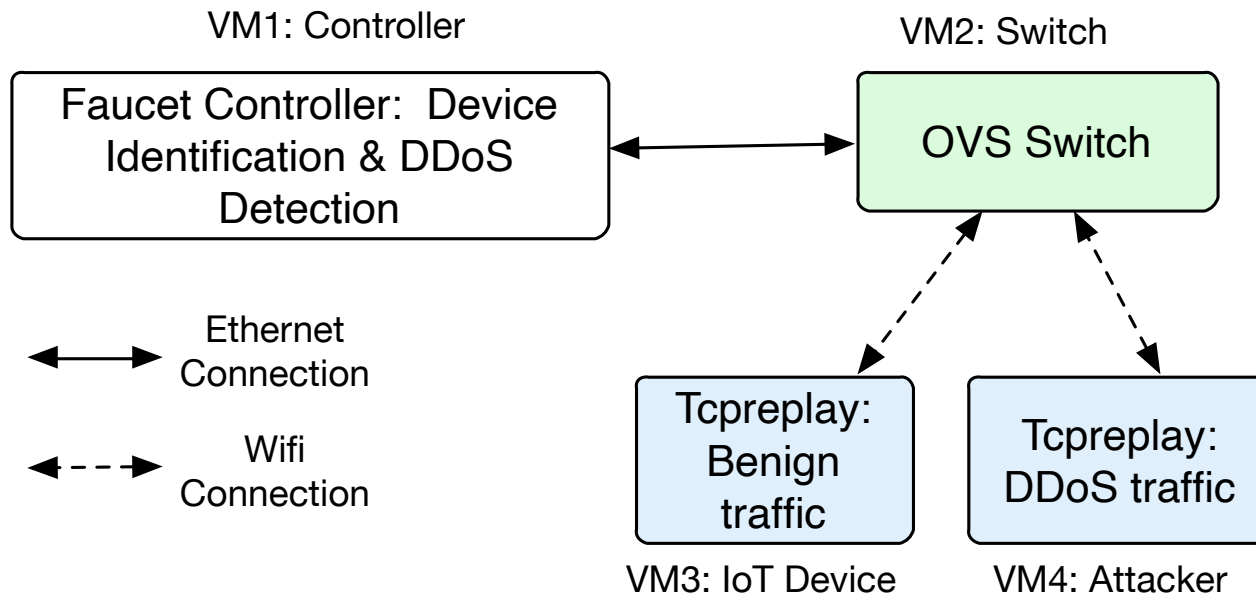
Smart Home network for benign and DDoS data collection

Datasets used

- To confirm the robustness of machine learning models —
 - used 3 datasets: SIOTLAB (our lab), UNSW dataset, combined dataset (SIOTLAB and UNSW)

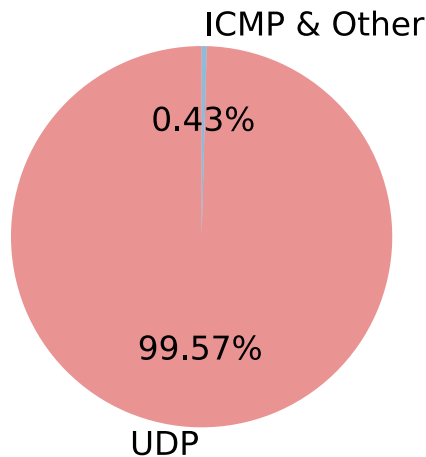
Device Category	Device
Switches /Triggers	WeMo Motion Sensor, TP Link Plug, Chromecast, Amazon Alexa, Nest Home Alert System
Camera Systems	Ring Cam, Nest Cam, Samsung Cam, Chromecast
IoT Hub Devices	Amazon Echo, IFix, Huebulb, iHome, Google Home

GNS3 Environment

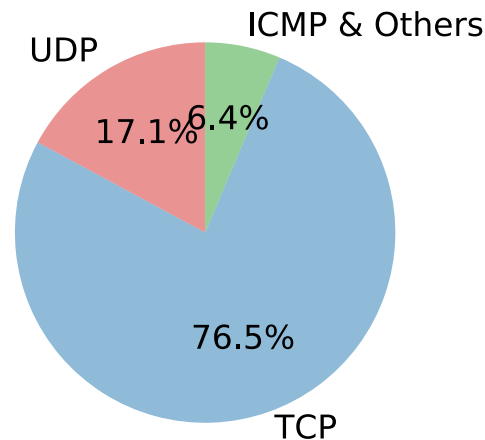


Virtual SDN-based smart home environment using GNS3 simulator

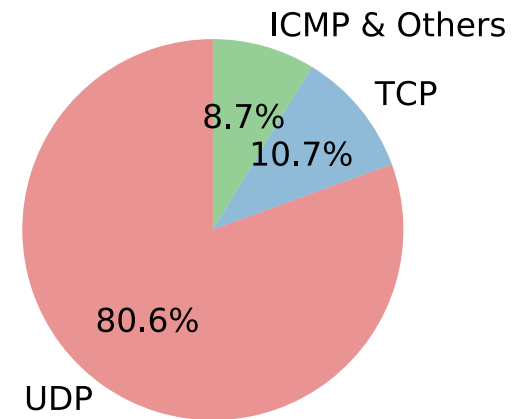
Proposed Flow-based Features



(a) Switches/Triggers



(b) Camera Systems

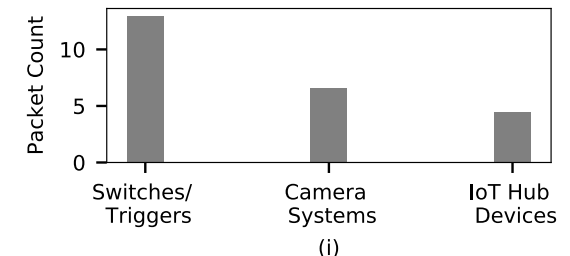
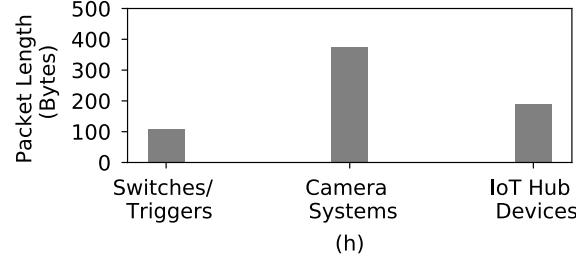
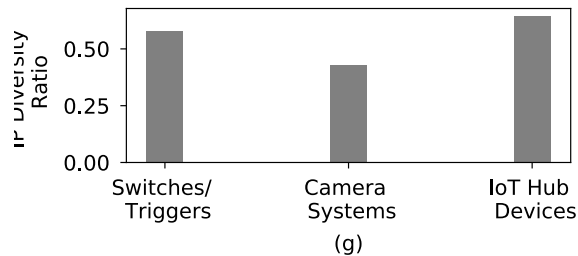
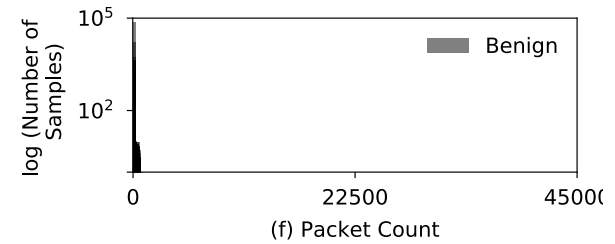
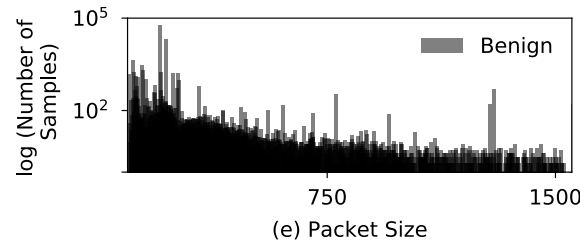
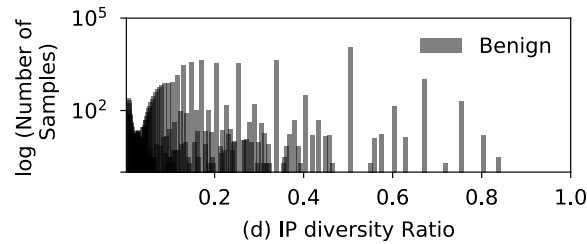
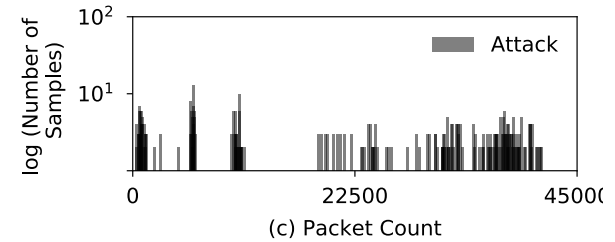
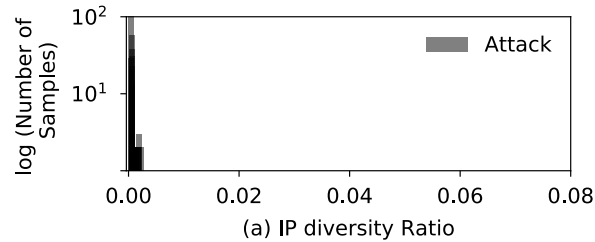


(c) IoT Hub Devices

The distinct difference between the distribution of TCP, UDP, ICMP, and other flows among device types enables us to successfully classify devices

Proposed Testing Environment

Proposed Flow-based Features

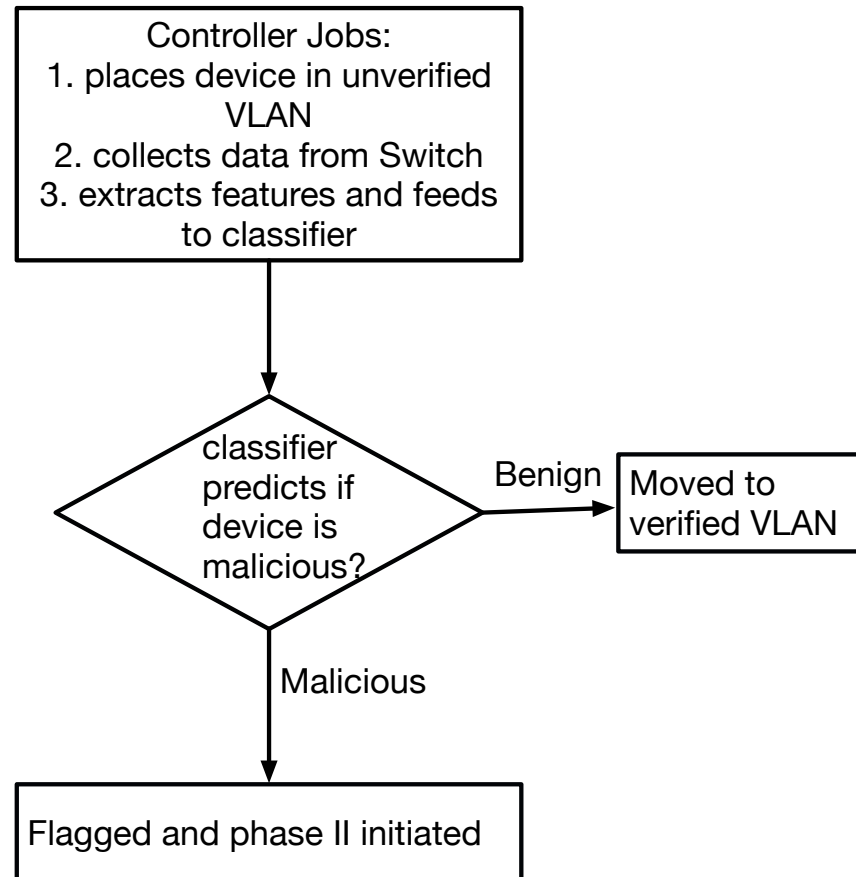


The higher shift in IP diversity ratio, packet size, and packet count allows us to classify devices and identify DDoS attacks with accuracy of 95%.

Proposed Secure Home Architecture

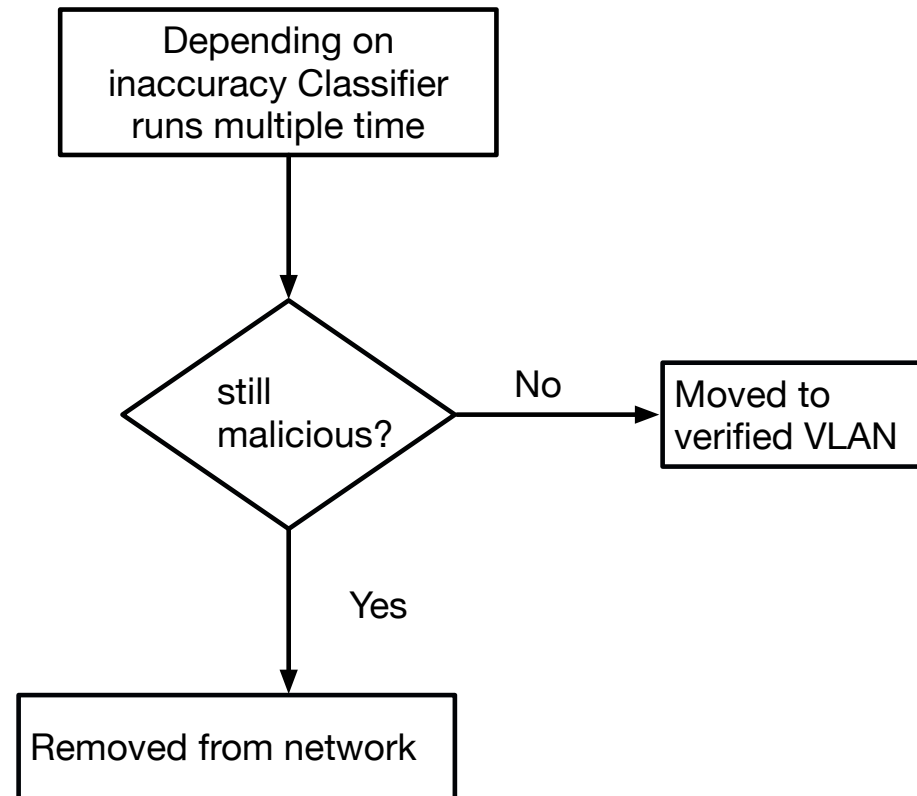
Phase I

Proposed architecture has two phases —



Phase I

Phase II



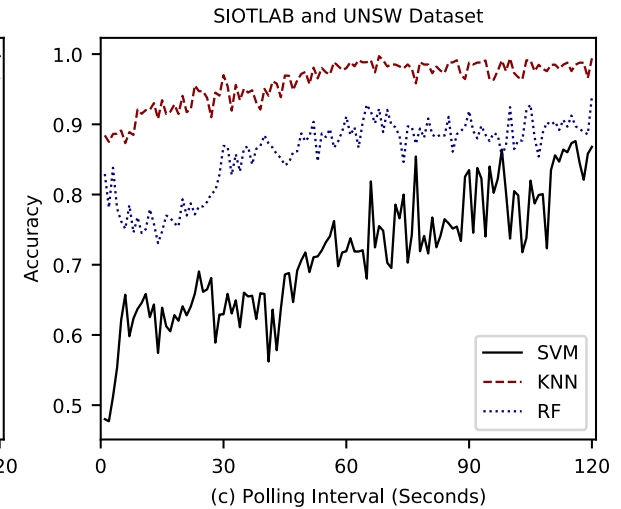
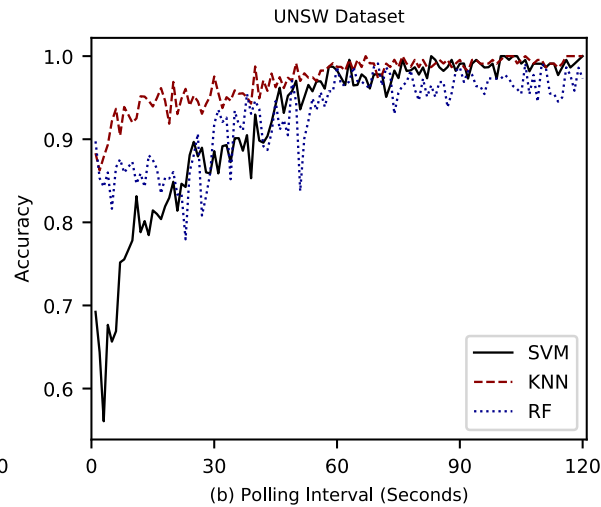
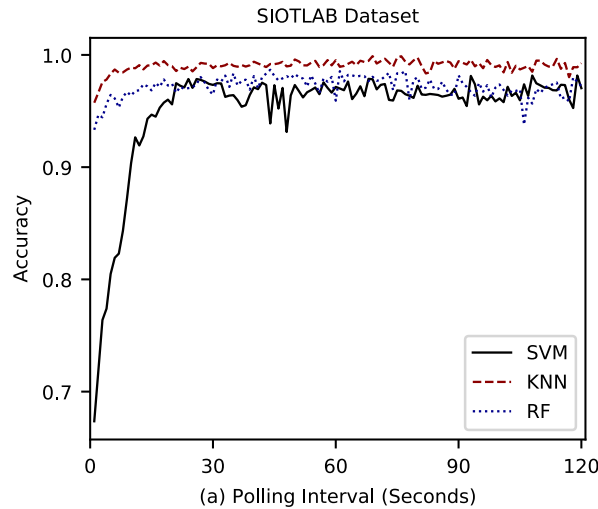
Phase II

Machine learning algorithms

- Machine Learning algorithms used —
 - K-Nearest Neighbors algorithm (KNN)
 - Support Vector Machine with linear kernel (LK-SVM)
 - Random Forest using Gini impurities (RF)
- Hyperparameters are default.
- Split data into 75% train and 25% test data.
- Classes are balanced.

Result and Discussion

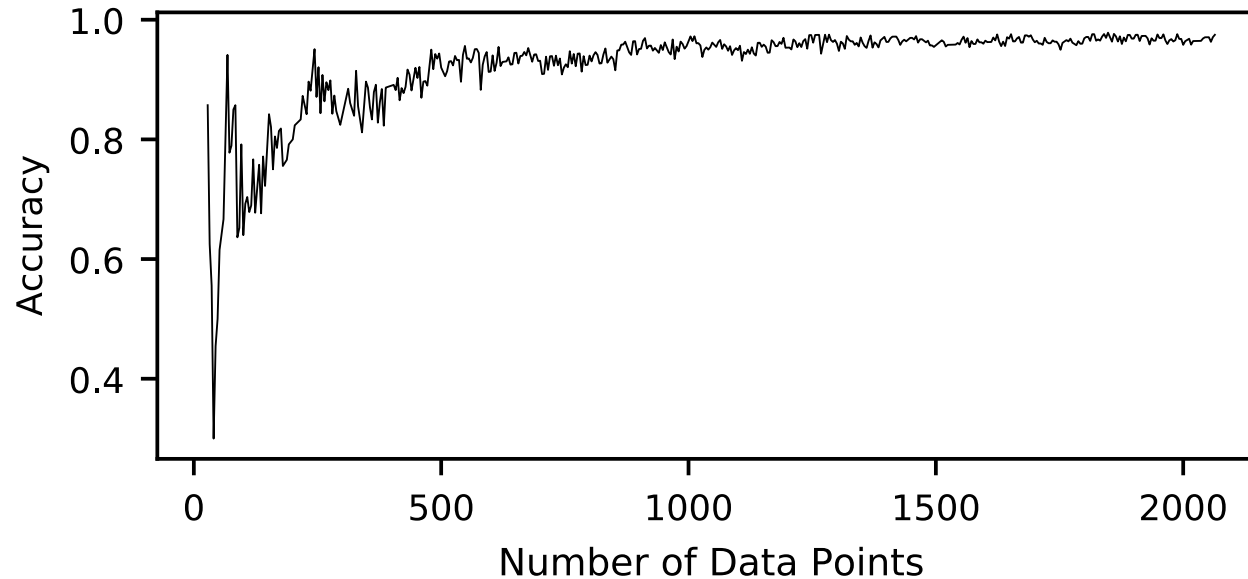
Machine learning algorithms performance



Accuracy of KNN, RF, and LK-SVM for SIOTLAB dataset, UNSW's dataset, and a combination of both datasets improves with increase in polling interval

Result and Discussion

Optimal polling interval



For combined dataset KNN shows 95% accuracy for 1820 data points, meeting the low memory requirement for IoT devices with high accuracy

Result and Discussion

Comparison with existing work

Existing work	Accuracy	Detection type	Dataset	Storage	Latency	Feature Count
[1]	97.5%	DDoS	UNSW	Yes	Yes	30
[2]	91.2%	Classification	Tor & Custom	No	Yes	6
[3]	96.37%	Classification	3 dataset	No	No	87
[4]	87.8%	Classification	Custom	No	Yes	15
[5]	99.8	DDoS	KD99	No	No	41
[6]	99.8%	DDoS	Custom	No	No	11
Proposed	99.9%	Classification & DDoS	Custom & UNSW	Yes	Yes	6

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Thank you!

Q & A