Botnet Detection on IoT Devices

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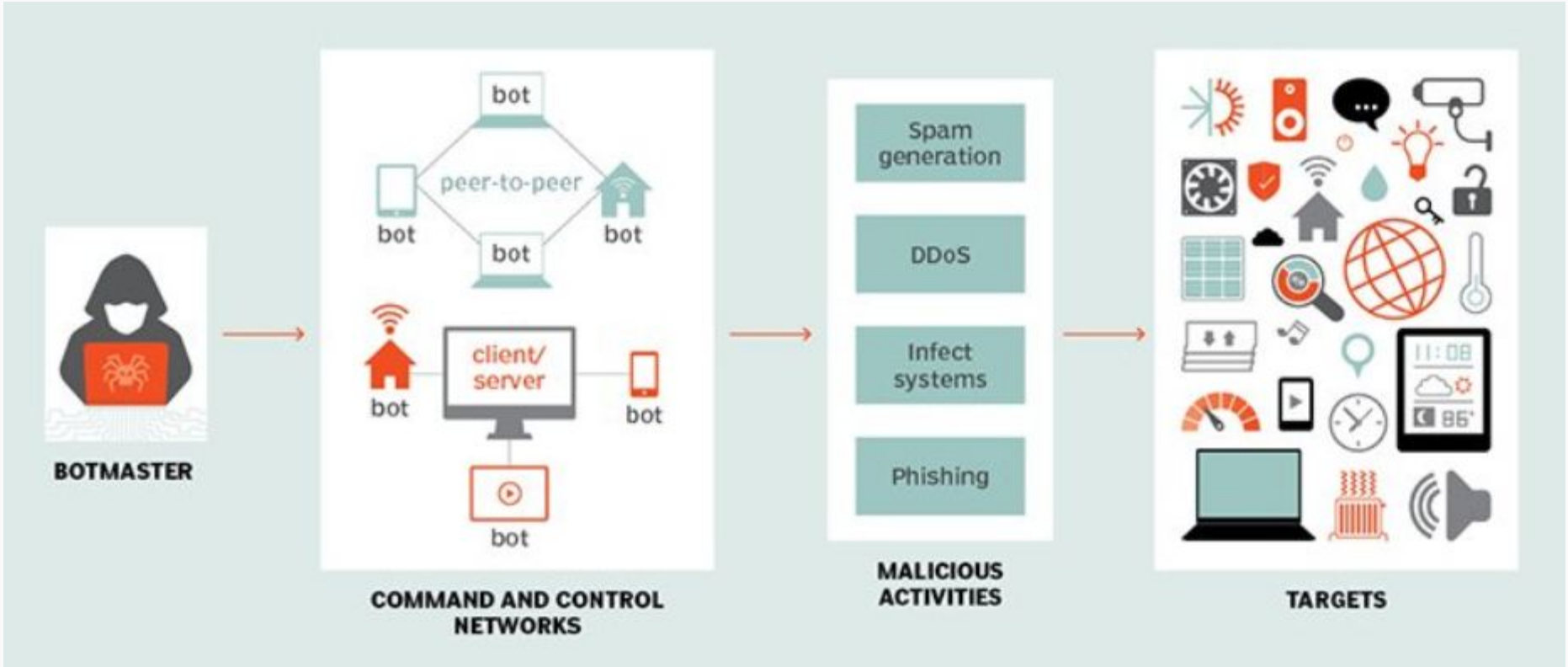
Data Science Capstone project - Springboard

The Problem

- Past **2 years DDoS attacks** has risen by **20%** & the scale and severity of their impact have risen by nearly **200%.**
- Sharp rise in protocol DDoS attacks.
- Increasing number of IoT devices are increasing the risk of DDoS attacks.
- 5G will fuel botnet-driven DDOS attacks in upcoming years.

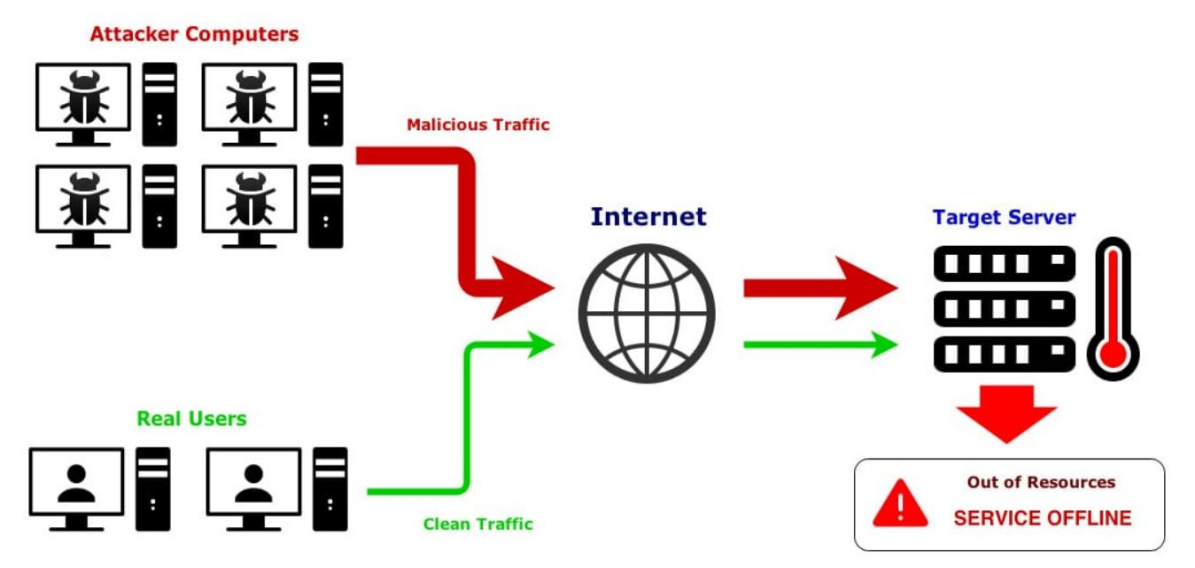
1. https://cybersecurityventures.com/the-15-top-ddos-statistics-you-should-know-in-2020/
2. https://www.indusface.com/blog/ddos-attack-trends/

What is Botnet?



https://cdn.ttgtmedia.com/rms/onlineImages/security-botnet_architecture_desktop.jpg

What is DDoS?



Distributed Denial-of-service

1. https://www.cloudflare.com/en-gb/learning/ddos/what-is-a-ddos-attack/

Who might care?

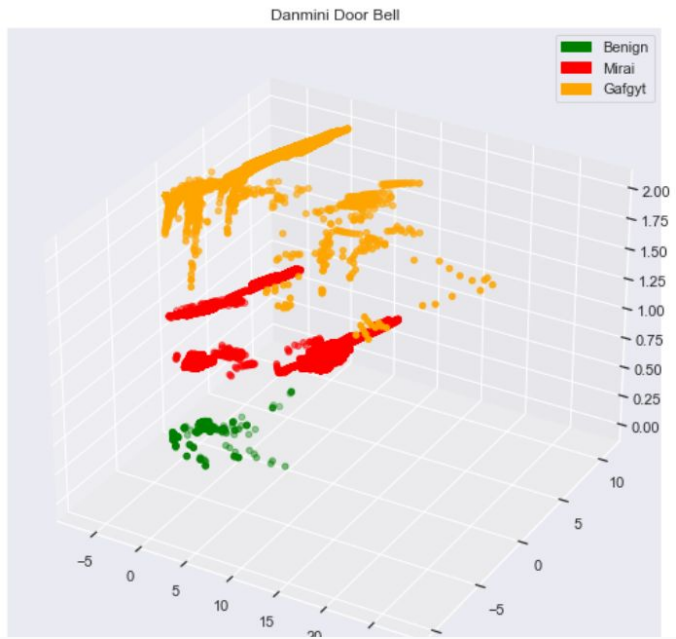
- Cyber security firms.
- Large financial / corporate enterprises.
- IoT Device Manufacturers.
- Anyone who uses internet !

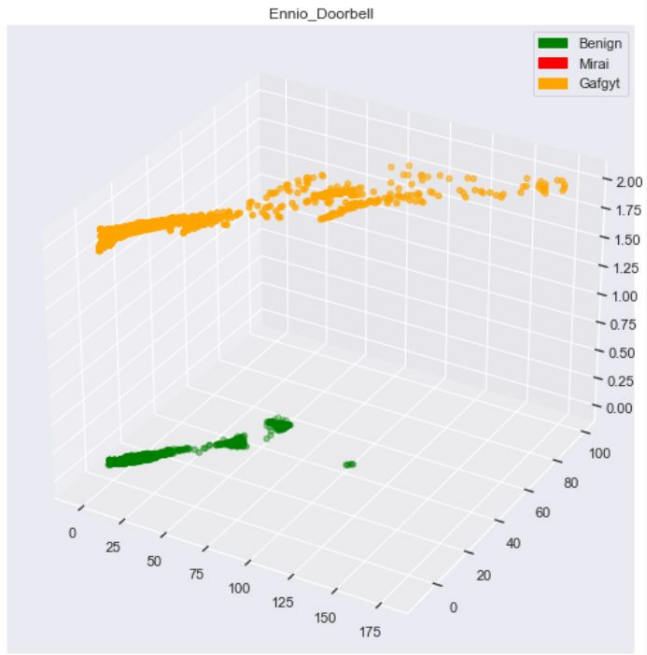
Data

- 2 type of Malware - Mirai , Bashlite
- 5 Categories and 9 IoT Devices - Baby monitor, Webcam, Security Camera, Doorbell, Thermostat
- Set of 23 features with 100ms, 500ms, 1.5sec, 10sec, 1 min time interval.
- Summary statistics - network snapshot of the device.

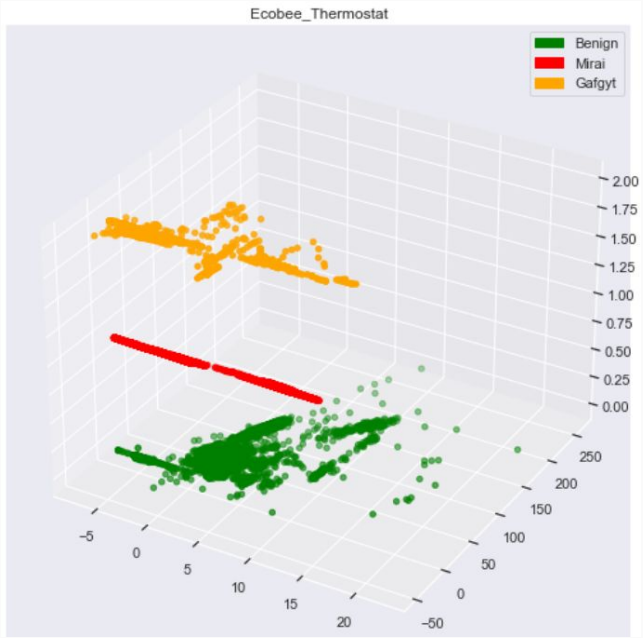
https://archive.ics.uci.edu/ml/datasets/detection_of_IoT_botnet_attacks_N_BaIoT.

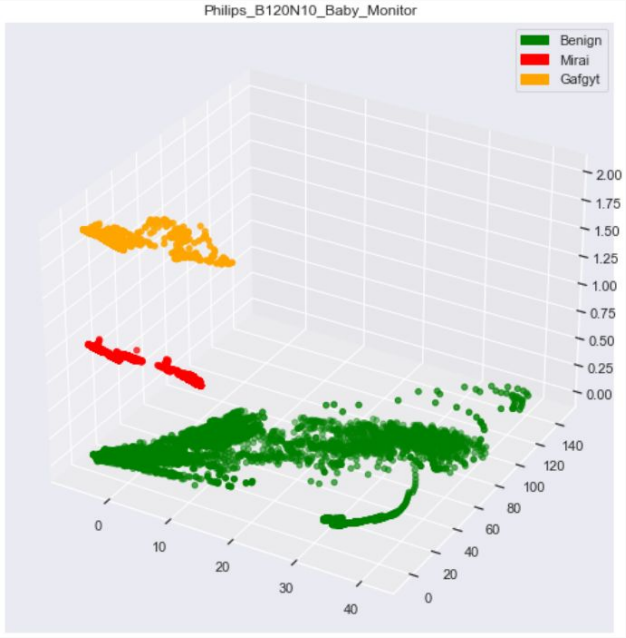
Data - Doorbell



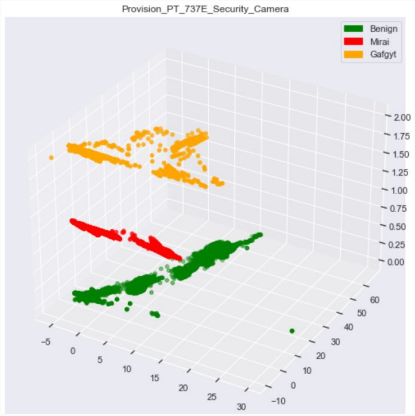


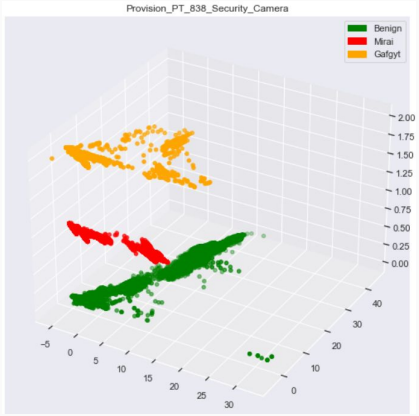
Data - Baby monitor & Thermostat

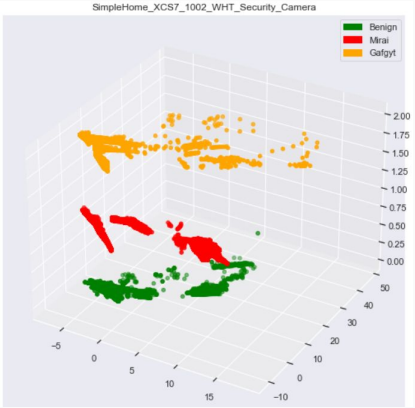


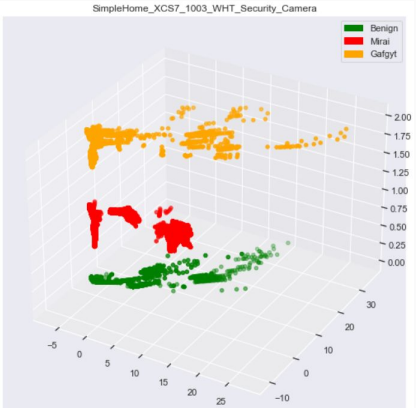


Data - Security cam









Modeling

- Supervised Learning
- 3 class & 11 class
- Highly imbalanced data
- Scikit learn and imblearn

- Label Encoding
- Data splitting into training and test data (70% - 30%)
- Classifier training using optimal parameters and 70% of the whole data
- Performance evaluation using holdout dataset (30% of the whole data)

Model comparisons - Danmini Door bell

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
0	Random Forest Classifier	1.0000	0.0	0.9999	1.0000	1.0000	0.9999	0.9999	2.8086
1	Decision Tree Classifier	0.9998	0.0	0.9997	0.9998	0.9998	0.9997	0.9997	21.2064
2	K Neighbors Classifier	0.9980	0.0	0.9935	0.9980	0.9980	0.9960	0.9960	25.6996
3	Ridge Classifier	0.9969	0.0	0.9958	0.9969	0.9969	0.9936	0.9936	1.2116
4	Ada Boost Classifier	0.9245	0.0	0.9202	0.9340	0.9216	0.8392	0.8522	144.0179
5	Quadratic Discriminant Analysis	0.6834	0.0	0.8271	0.8491	0.6724	0.4799	0.5712	5.3659
6	Naive Bayes	0.6585	0.0	0.3543	0.7312	0.5410	0.0693	0.1829	0.8091
7	SVM - Linear Kernel	0.4204	0.0	0.3930	0.4682	0.3959	0.0762	0.1060	6.0382
8	Logistic Regression	0.0486	0.0	0.3333	0.0024	0.0045	0.0000	0.0000	4.2906

Logistic Regression is the worst and **Random forest classifier** is the best

Model Result - Random Forest

Random Forest Classifier - F1 Score

Device	All data with 3 Classes	Under sampled data with 3 classes	All data with 11 Classes	Under sampled data with 11 Classes
Danmini Doorbell	1.0	1.0	1.0	1.0
Ecobee Thermostat	1.0	1.0	0.998	0.988
Ennio Doorbell	1.0	1.0	0.992	0.983
Philips B120N10 Baby Monitor	1.0	1.0	0.997	0.989
Provision PT 737E Security Camera	1.0	1.0	0.993	0.981
Provision PT 838 Security Camera	1.0	1.0	1.0	1.0
Samsung SNH 1011 N Webcam	1.0	1.0	0.999	0.998
SimpleHome XCS7 1002 WHT Security Camera	1.0	1.0	1.0	1.0
Simple Home XCS7 1003 WHT Security Camera	1.0	1.0	0.993	0.970

Model Result - Decision Tree

Decision Tree Classifier - F1 Score

Device	All data with 3 Classes	Under sampled data with 3 classes	All data with 11 Classes	Under sampled data with 11 Classes
Danmini Doorbell	1.0	1.0	0.865	0.574
Ecobee Thermostat	0.997	1.0	0.925	0.770
Ennio Doorbell	0.999	1.0	0.945	0.983
Philips B120N10 Baby Monitor	1.0	1.0	0.857	0.878
Provision PT 737E Security Camera	1.0	1.0	0.781	0.859
Provision PT 838 Security Camera	1.0	1.0	0.799	0.877
Samsung SNH 1011 N Webcam	1.0	1.0	0.892	0.998
SimpleHome XCS7 1002 WHT Security Camera	0.996	1.0	0.913	0.648
Simple Home XCS7 1003 WHT Security Camera	0.997	1.0	0.915	0.847

Assumptions, Limitations

- Model - Individual devices
- New Device - Train model again
- Model training - only network traffic data
- Deployment - Need optimization
- Data - Only current version of malware

Improve the model in future

- Develop Generic model.
- Trained with both network traffic and device action data.
- Convert model into device firmware and deploy into edge device.
- Malware constantly evolve, need to update the model when new vulnerability found on the internet

Conclusions

- Random forest model performed well compare to other supervised learning model.
- All 115 features used to train the model since malware can attack the device on different time interval
- 70%-30% Splitting the test data gave F1 score of 1.0
- Constant monitoring of the malware, the model can be improved in the future.

Thank you!

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https://github.com/dineshh912