

Mitigating DDoS Attacks and Ensuring Service Availability

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Agenda

- Introduction
- Business Problem
- Proposed Solution
- Success Metrics
- Data
- Model Selection & Results
- Conclusions
- Validation
- Further Work

Introduction

What is a DDoS attack?

- Distributed Denial of Service (DDoS)
- Swamp a target service/network/infrastructure with junk traffic
- 'Bots' organized into 'botnets', directed by attacker
- Any internet-connected device can be compromised and co-opted

Home > News > Security

Botnet Generates One of the Largest DDoS Attacks on Record

The attack, which targeted an unnamed financial provider, was mitigated without any human intervention, according to Cloudflare.



By Michael Kan

August 19, 2021



A Casino Gets Hacked Through a Fish-Tank Thermometer

Are your fish tanks secure?

By Gene Marks

Updated: June 1, 2021

'Smart' home devices used as weapons in website attack

© 22 October 2016

Why are DDoS attacks a problem worth solving?

- Directed at all industries
- For all kinds of reasons
- Inexpensive
- ‘Traditional’ DDoS damages
- Ransom, Extortion-based attacks
- More commonplace, evolving rapidly

GEOPOLITICS

As Russia invades, Ukrainian government networks suffer high-profile DDoS disruption

Last night, GitHub was hit with massive denial-of-service attack from China

By Russell Brandom | Mar 27, 2015, 10:53am EDT
Source [Insight Labs](#) | Via [Motherboard](#)

Major banks hit with biggest cyberattacks in history

by David Goldman @DavidGoldmanCNN
September 28, 2012 9:27 AM ET

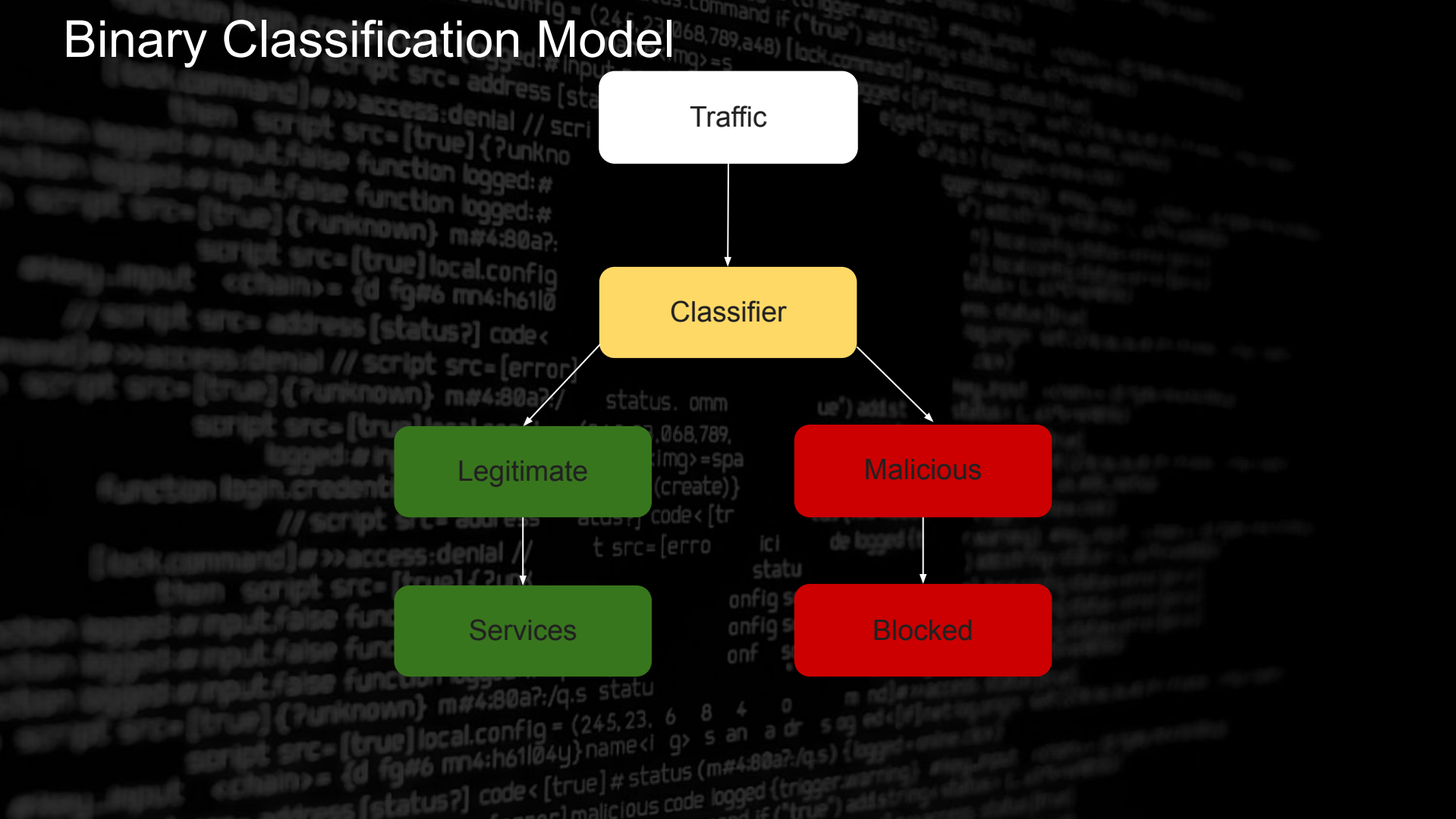


Business Problem

Mitigate the effects of a DDoS attack on business operations by identifying and blocking malicious traffic, thereby ensuring service availability for legitimate traffic.

Proposed Solution

Binary Classification Model



Success Metrics

Success Metrics

Business Terms:

- Minimize misidentification of legitimate traffic as malicious (ideally to **0**)
- Mitigate effects of DDoS attack by **90%**

Statistical Metrics:

- **Recall**: As close to **1.0** as possible
- **Precision**: Greater than or equal to **0.9**
- **F₂**: Optimizing metric for model selection

Data

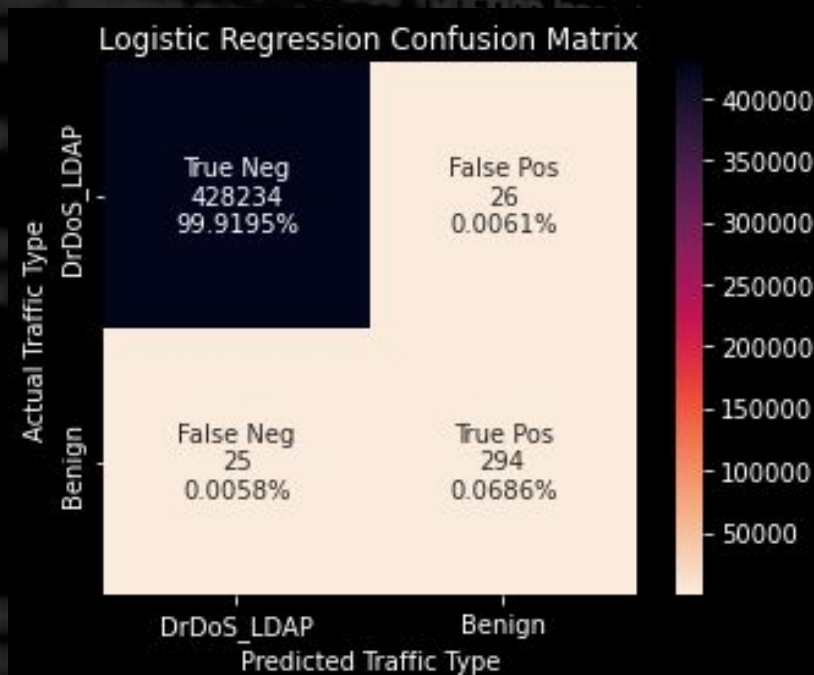
Data

- [DDoS Evaluation Dataset CIC 2019](#)
 - *With permission, Canadian Institute for Cybersecurity @ University of New Brunswick*
- Synthetic attack conducted using on-premise testbed with simulated benign interactions
- Dataset generated from .PCAP files containing packet information using [CICFlowMeter](#)
- 2,181,542 Observations
- 88 Features
- Heavily Imbalanced: 99.926% Malicious/0.073% Benign
- NaN/Infinity values dropped, traffic origination features removed
- Binary Labels
 - DrDoS_LDAP = Malicious
 - BENIGN = Legitimate

Model Selection & Results

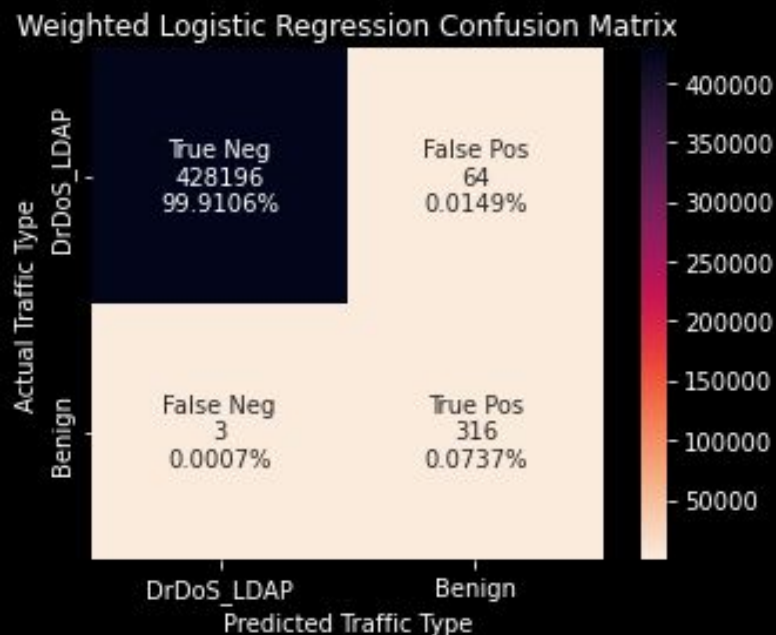
Logistic Regression

Baseline Model



F_2 : .921 Recall: .921 Precision: .918

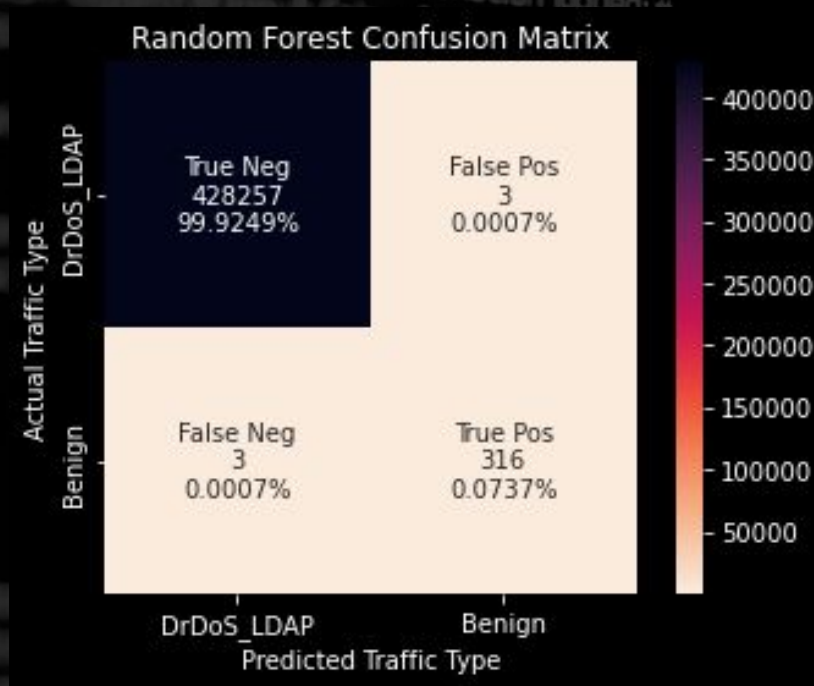
With Balanced Class Weights



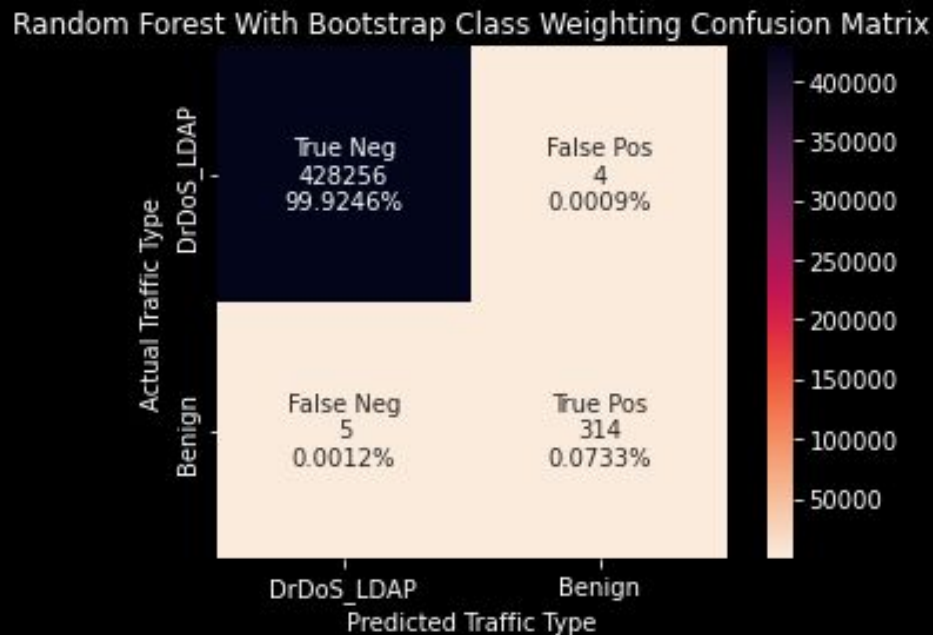
F_2 : .954 Recall: .990 Precision: .831

Random Forest

Baseline Model



With Bootstrap Class Weighting



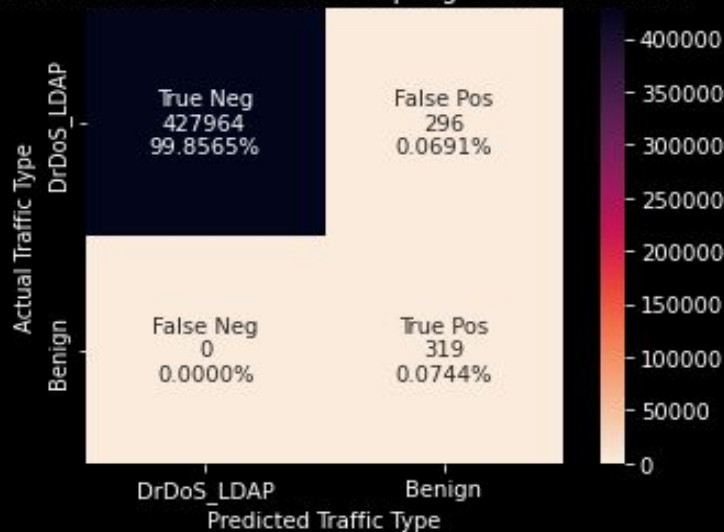
F_2 : .990 Recall: .990 Precision: .990

F_2 : .977 Recall: .974 Precision: .990

Imbalanced Random Forest

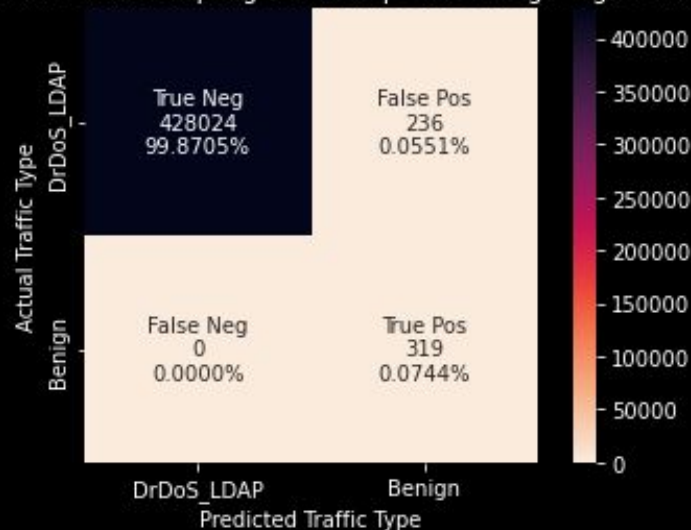
Baseline Model

Random Forest with Data Resampling Confusion Matrix



With Data Resampling & Bootstrap Class Weighting

Random Forest with Data Resampling (Bootstrap Class Weighting) Confusion Matrix

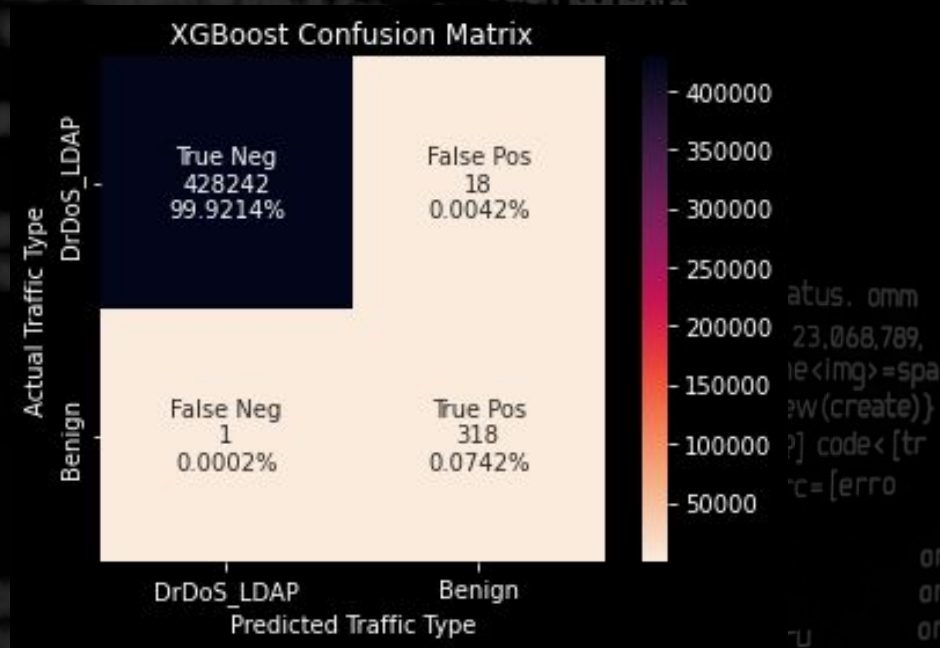


F_2 : .984 Recall: .984 Precision: .987

F_2 : .871 Recall: 1 Precision: .574

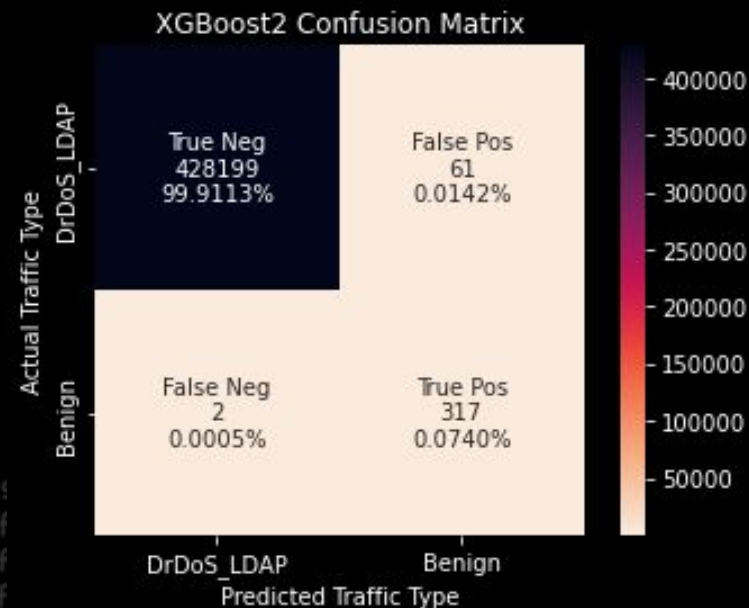
Gradient Boosted Trees (XGBoost)

Baseline Model



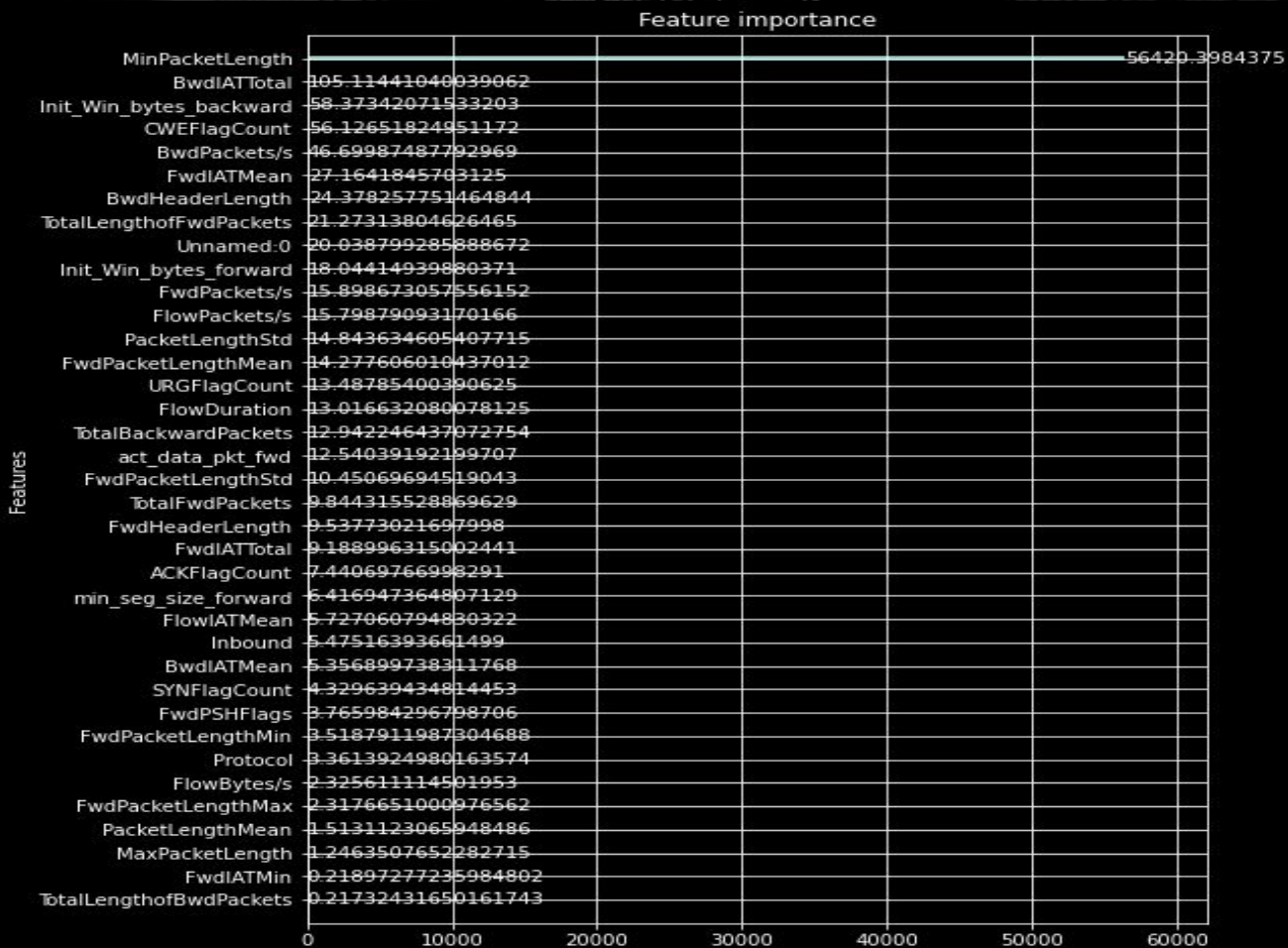
F_2 : .986 Recall: .996 Precision: .946

With Balanced Class Weights



F_2 : .958 Recall: .993 Precision: .838

XGBoost - Feature Importance by information gain



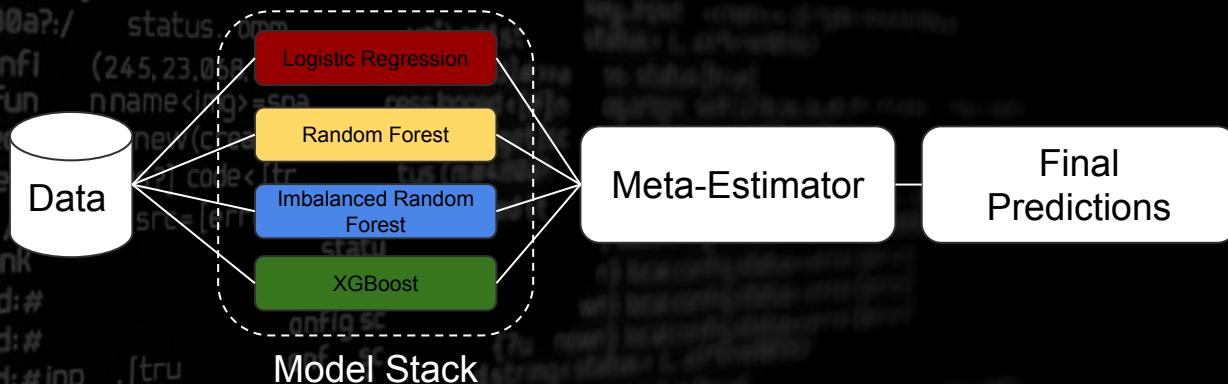
Ensembling

Final Models:

1. Weighted Logistic Regression
2. Baseline Random Forest
3. Imbalanced Random Forest with Bootstrap Class Weights
4. Baseline XGBoost

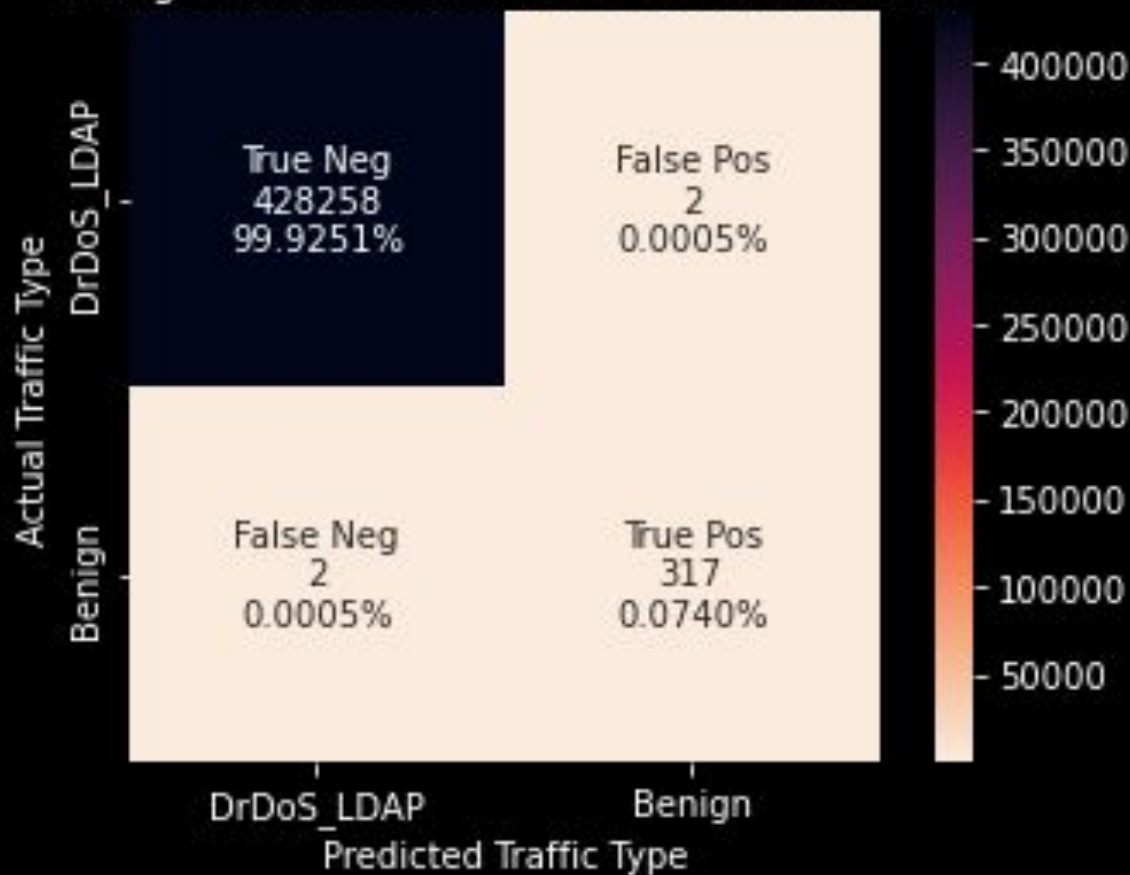
Methods Attempted:

1. Voting Classifier
2. Soft Voting Classifier
3. Stacked Classifier



Voting Classifier

Voting Classifier Ensemble Confusion Matrix



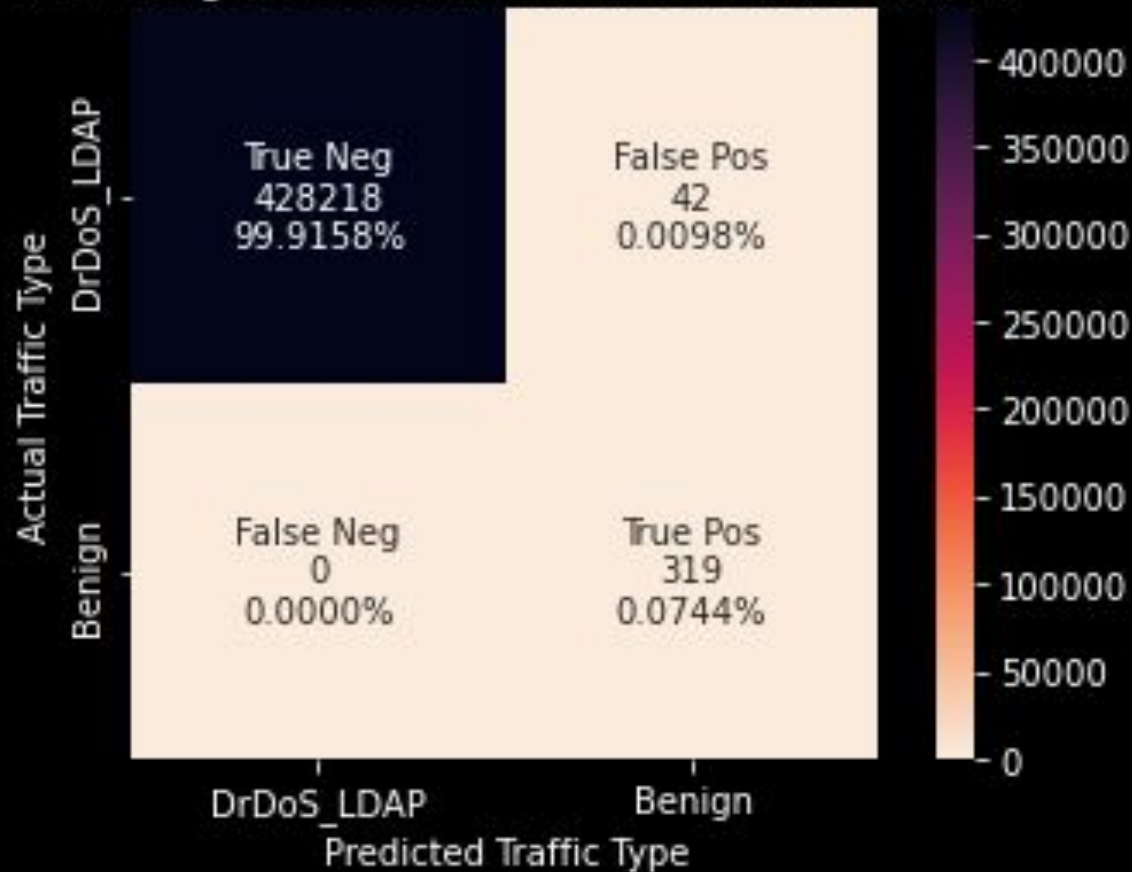
F_2 : .993

Recall: .993

Precision: .993

Soft Voting Classifier

Soft Voting Classifier Ensemble Confusion Matrix



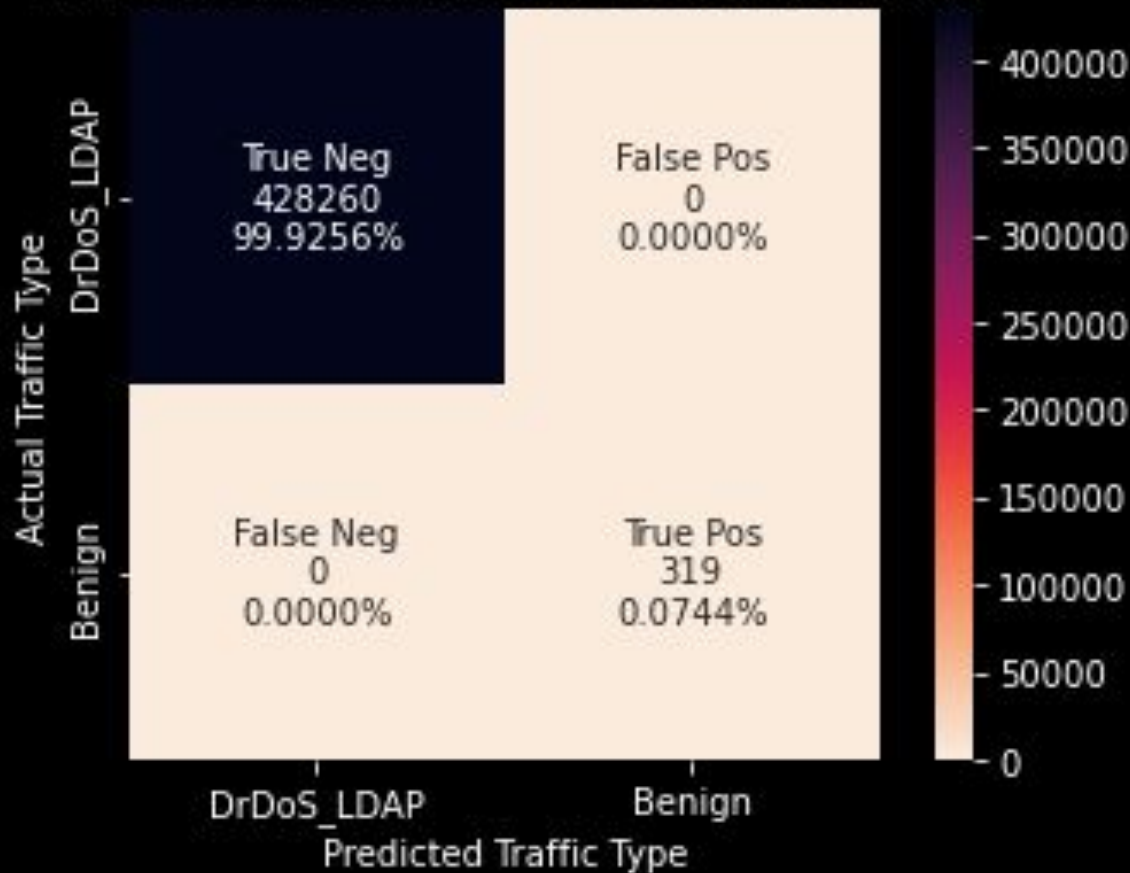
F_2 : .974

Recall: 1

Precision: .883

Stacked Classifier - Validation

Stacked Classifier Ensemble Confusion Matrix



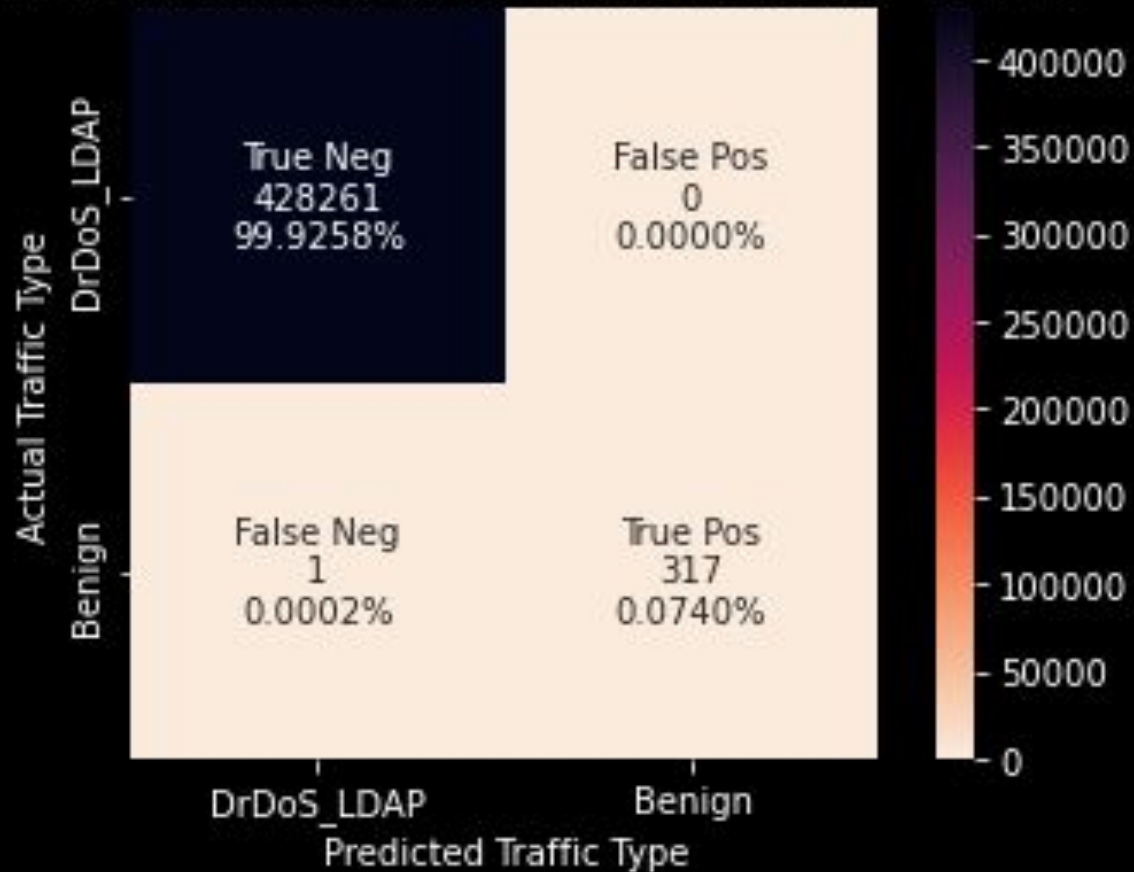
$F_2 : 1$

Recall: 1

Precision: 1

Stacked Classifier - Final Test Results

Stacked Classifier Ensemble Confusion Matrix - Test Set



F_2 : .997

Recall: .996

Precision: 1

Conclusions

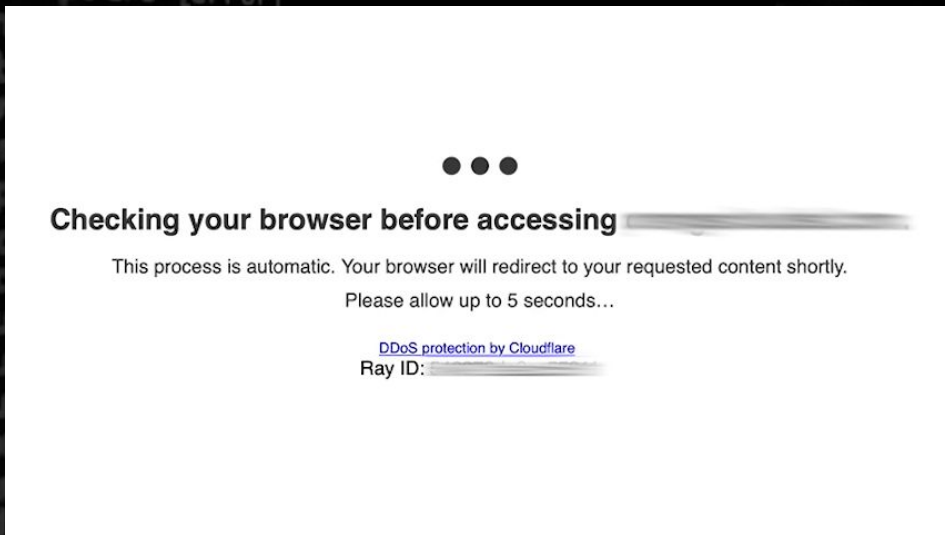
Conclusions

- Viability of using classification to identify malicious/legitimate traffic is proven
- Stacking Classifier Ensemble performs exceptionally well
 - Meets & exceeds business objectives/success metrics
- MinPacketLength traffic feature should be explored further

Validation

Validation

- Additional testing with synthetic attacks
- Deploy model in production
 - Evaluate recall rate on live benign traffic
 - Evaluate precision during DDoS attack
 - Benchmark performance against vendor solutions (e.g. Cloudflare, Akamai)



Further Work

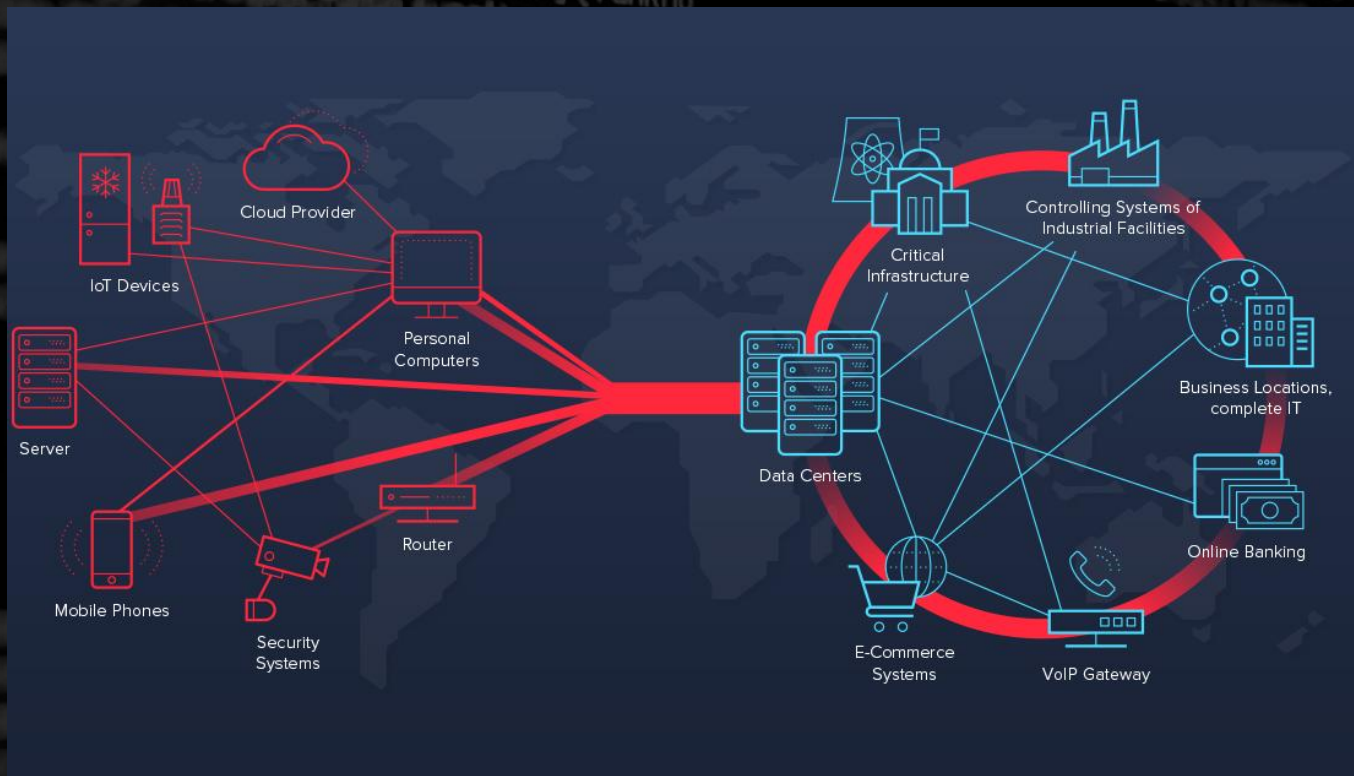
Further Work

- Expand to include more DDoS attack types
- Hyperparameter tuning for models/ensemble
- Reduce model training/prediction time using Dask, RAPIDS cuML
- Additional models in the ensemble (Naive Bayes)

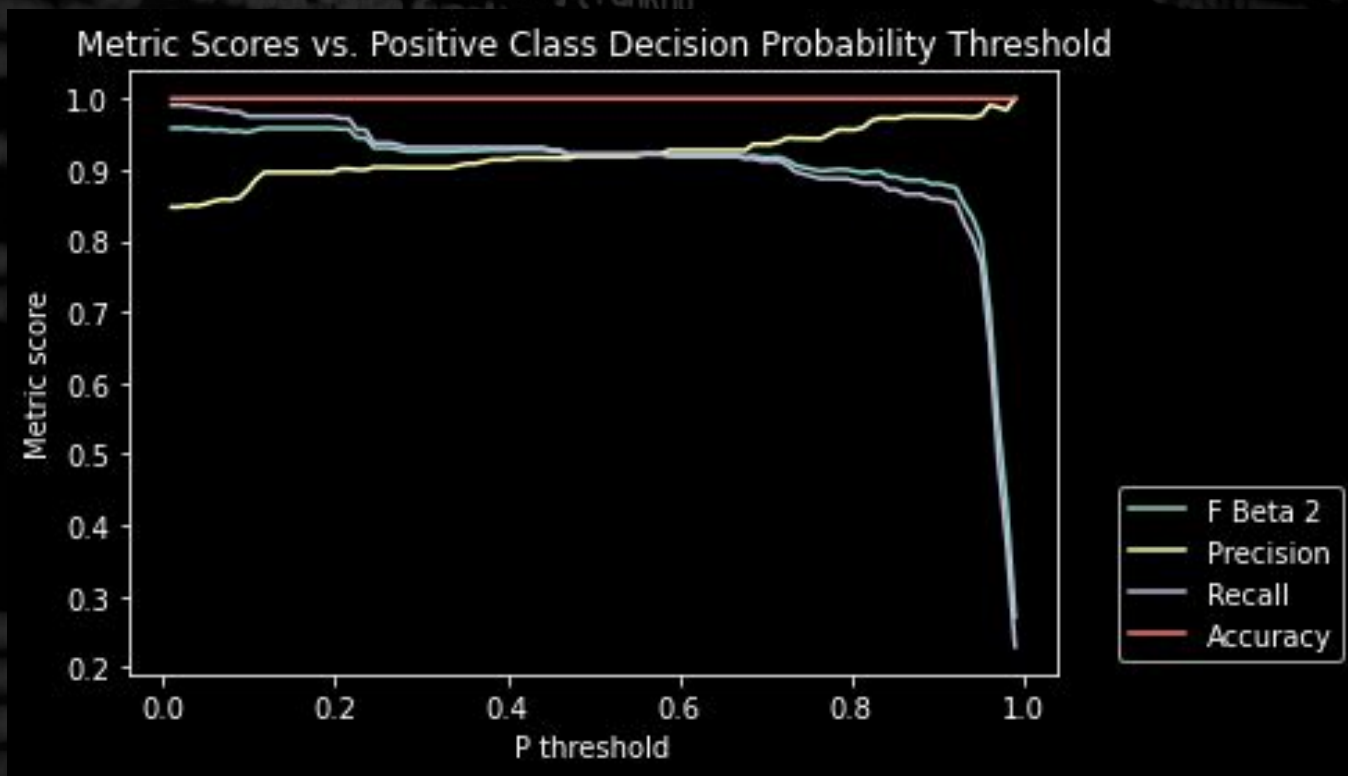
Thank you!

Appendix

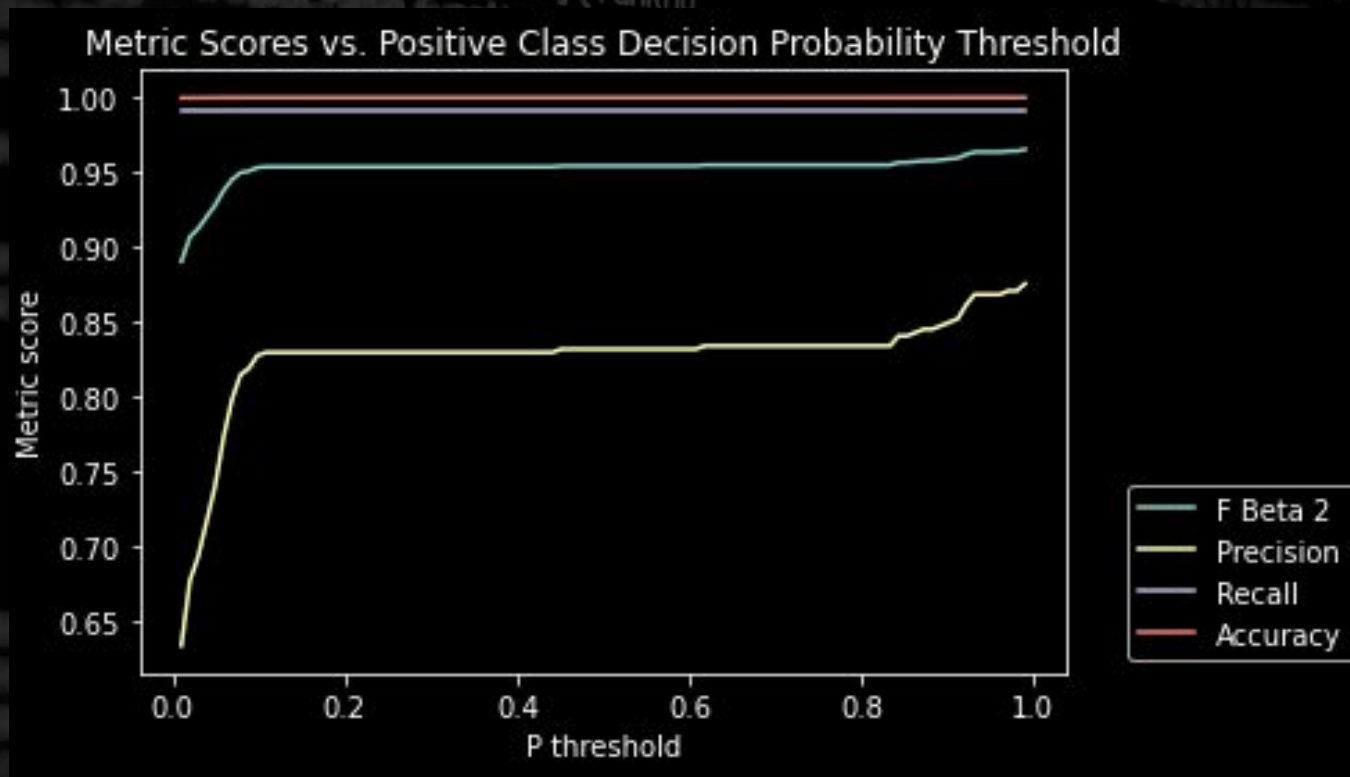
What is a DDoS attack?



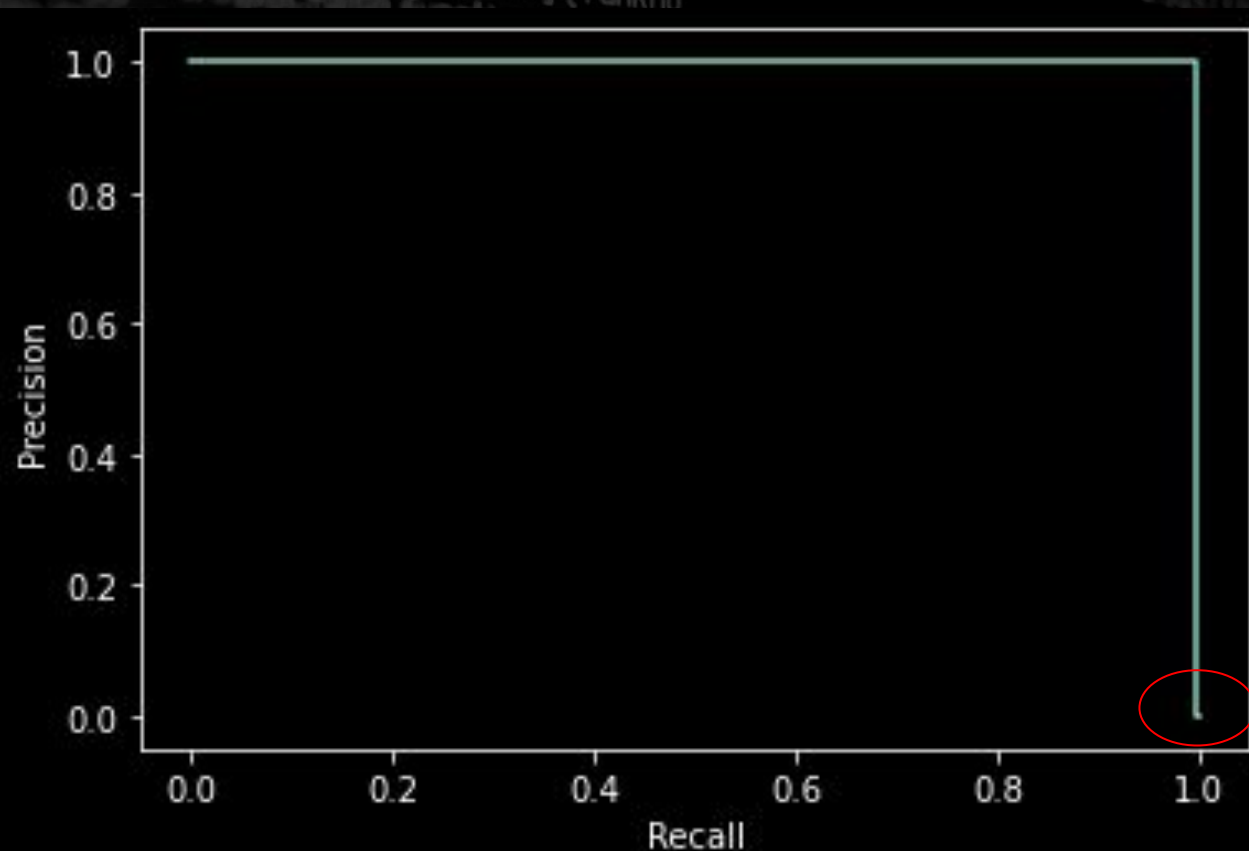
Baseline Logistic Regression Threshold



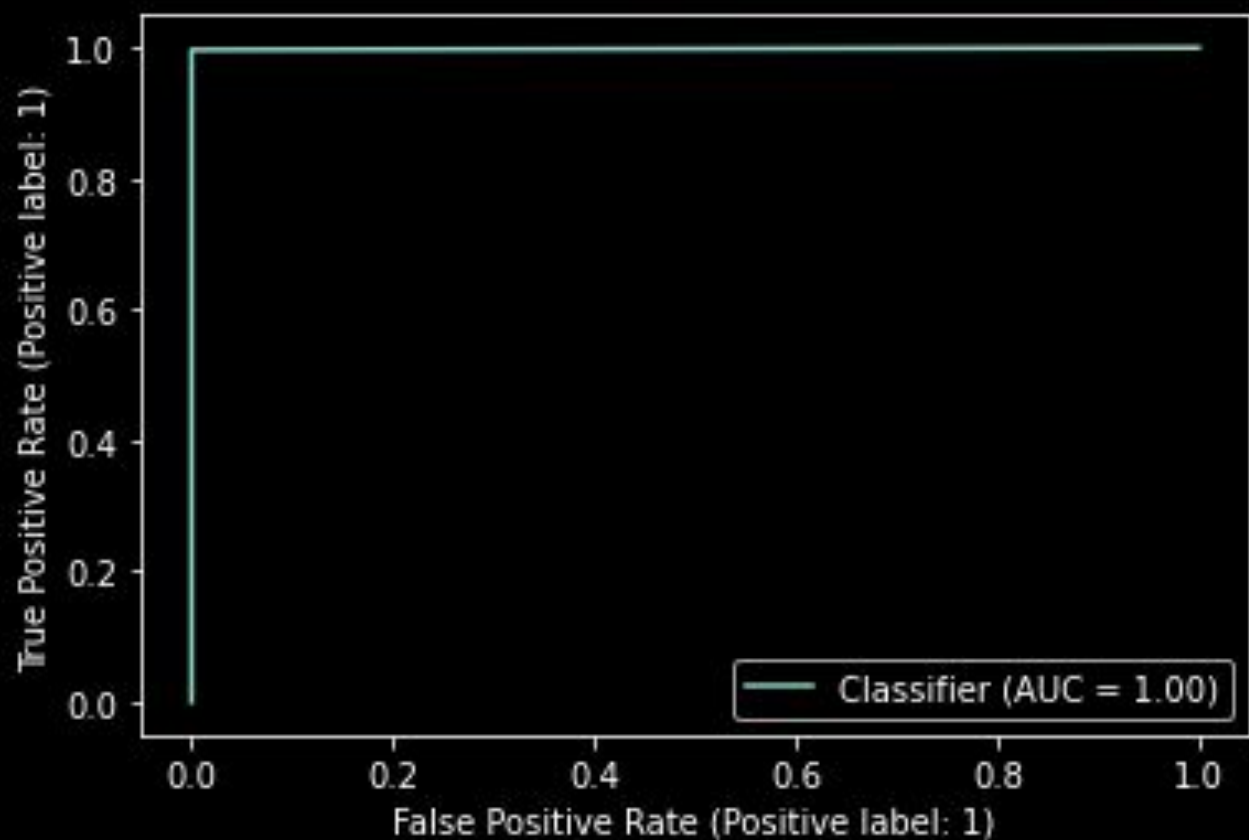
Weighted Logistic Regression Threshold



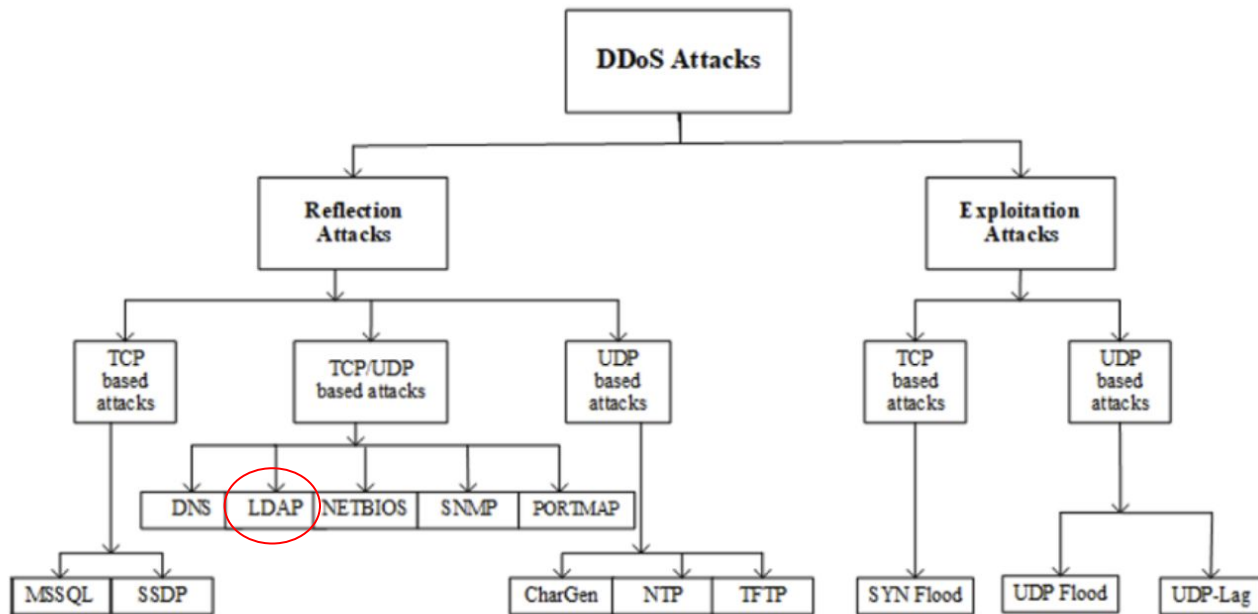
Stacked Classifier Precision/Recall Curve



Stacked Classifier ROC Curve



DDoS Attack Types



Testbed Architecture

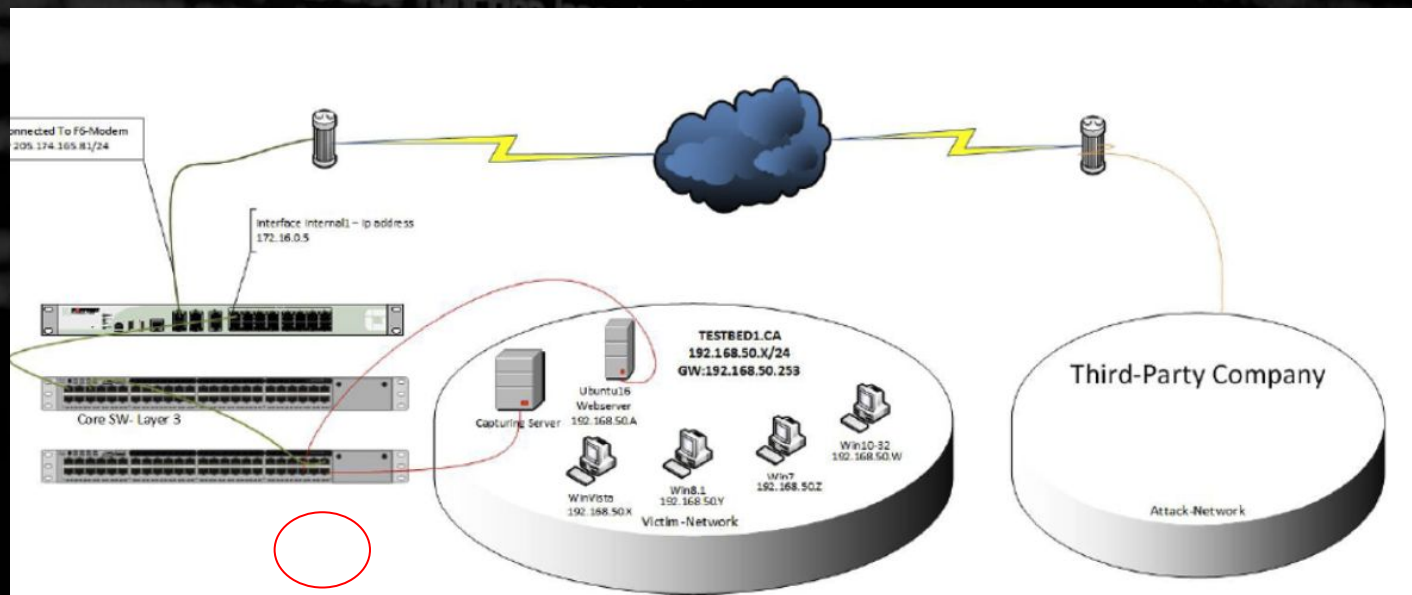


Figure 2: Testbed Architecture