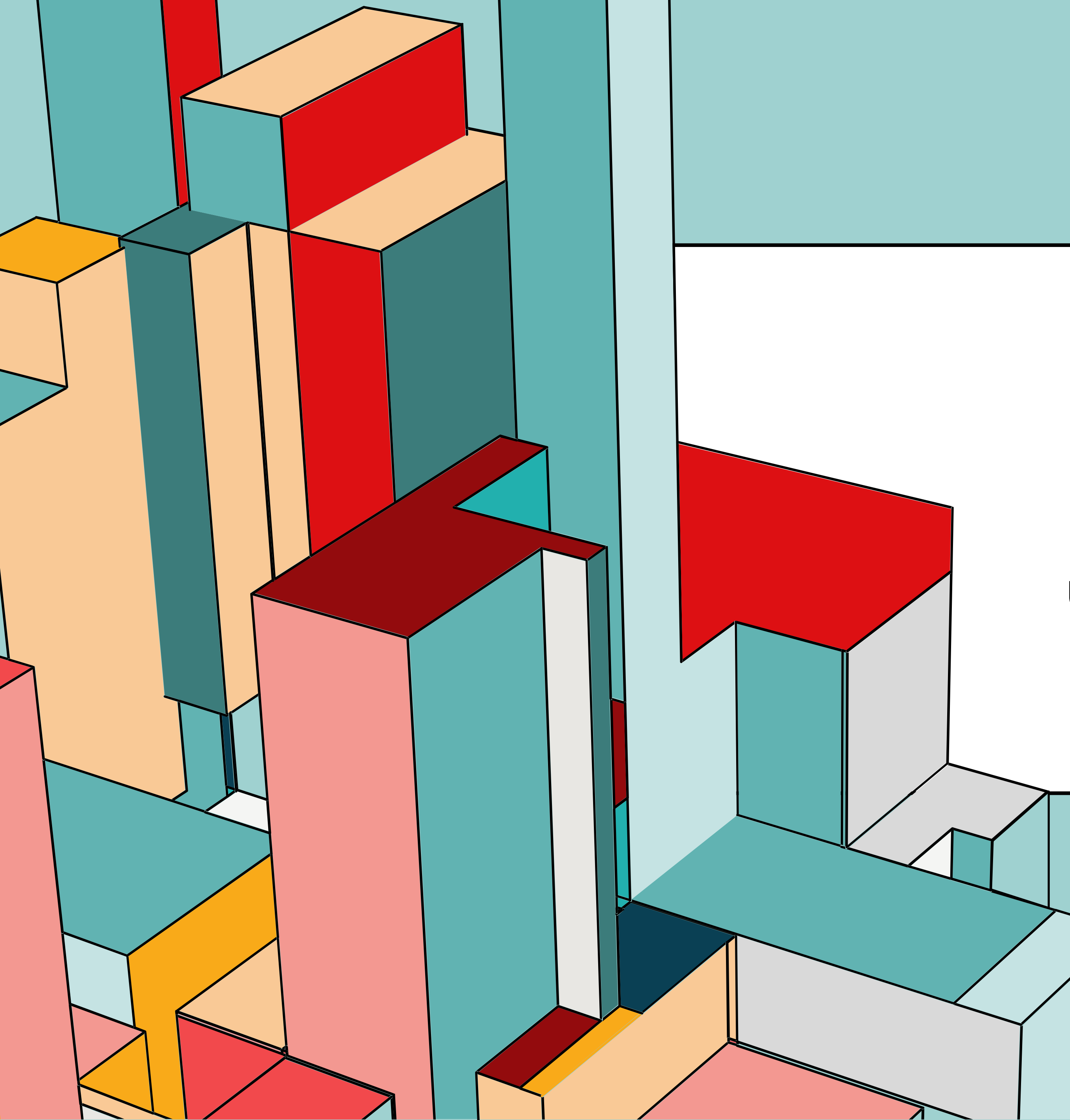


MALWARE DETECTION

Use for IoT Devices

Second Capstone Presentation

Springboard DSCT Bootcamp

Pablo Ruiz Lopez

PROBLEM IDENTIFICATION

STATEMENT

IoT has proven to have a significant impact on human life by the integration of devices in a myriad of industries. There will be around **125 IoT devices connected to the internet by 2030.**

Developing **deployable technology in the form of algorithms, frameworks or even complete SIEM Systems, could be extremely useful to get a better understanding of the behavior of malware infections** where IoT devices are the main target.

STAKEHOLDERS TO PROVIDE KEY INSIGHTS

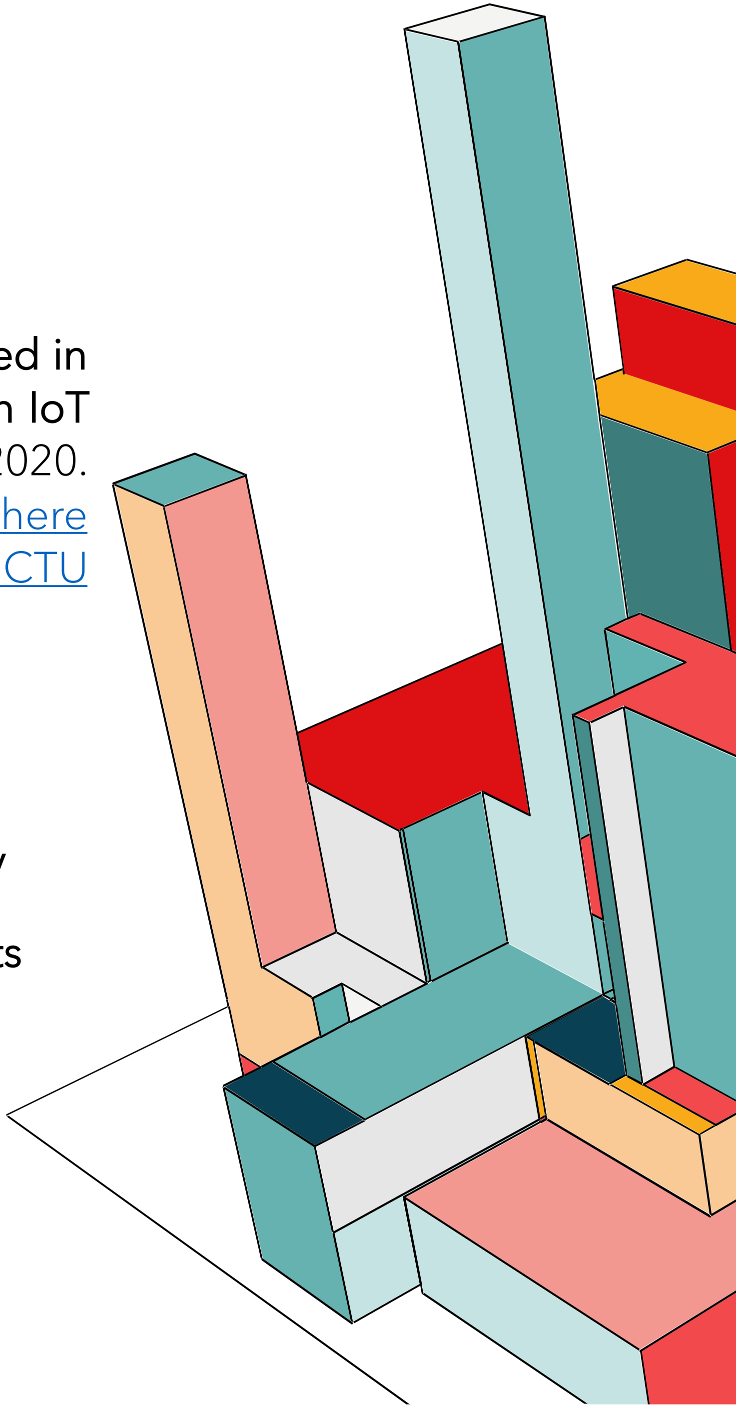
- Cyber Security Teams
- Antivirus Companies
- IoT Companies

SCOPE OF SOLUTION SPACE

Dataset: 20 malware captures executed in IoT devices, and 3 captures for benign IoT devices traffic. Published in January 2020. These were captured in the Stratosphere Laboratory, AIC group, FEL, CTU University, Czech Republic.

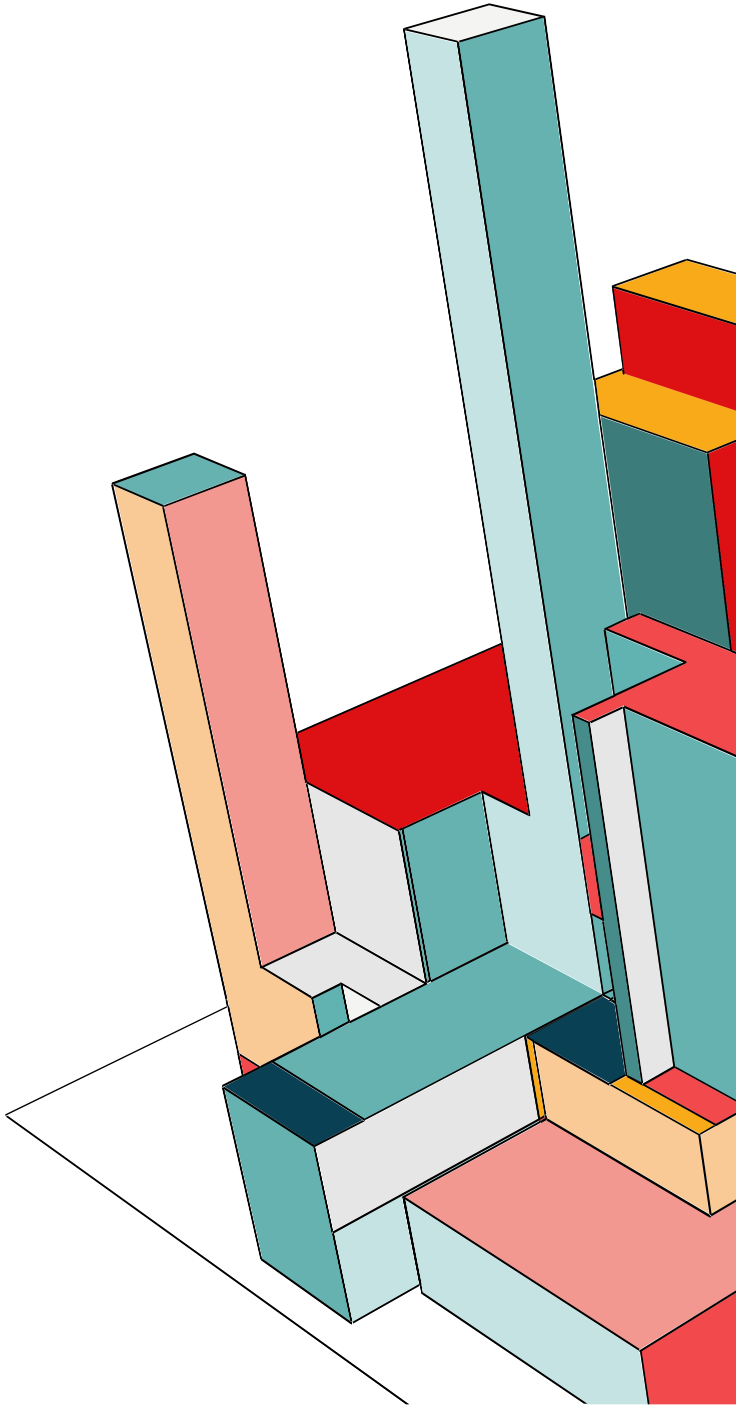
KEY DATA SOURCES

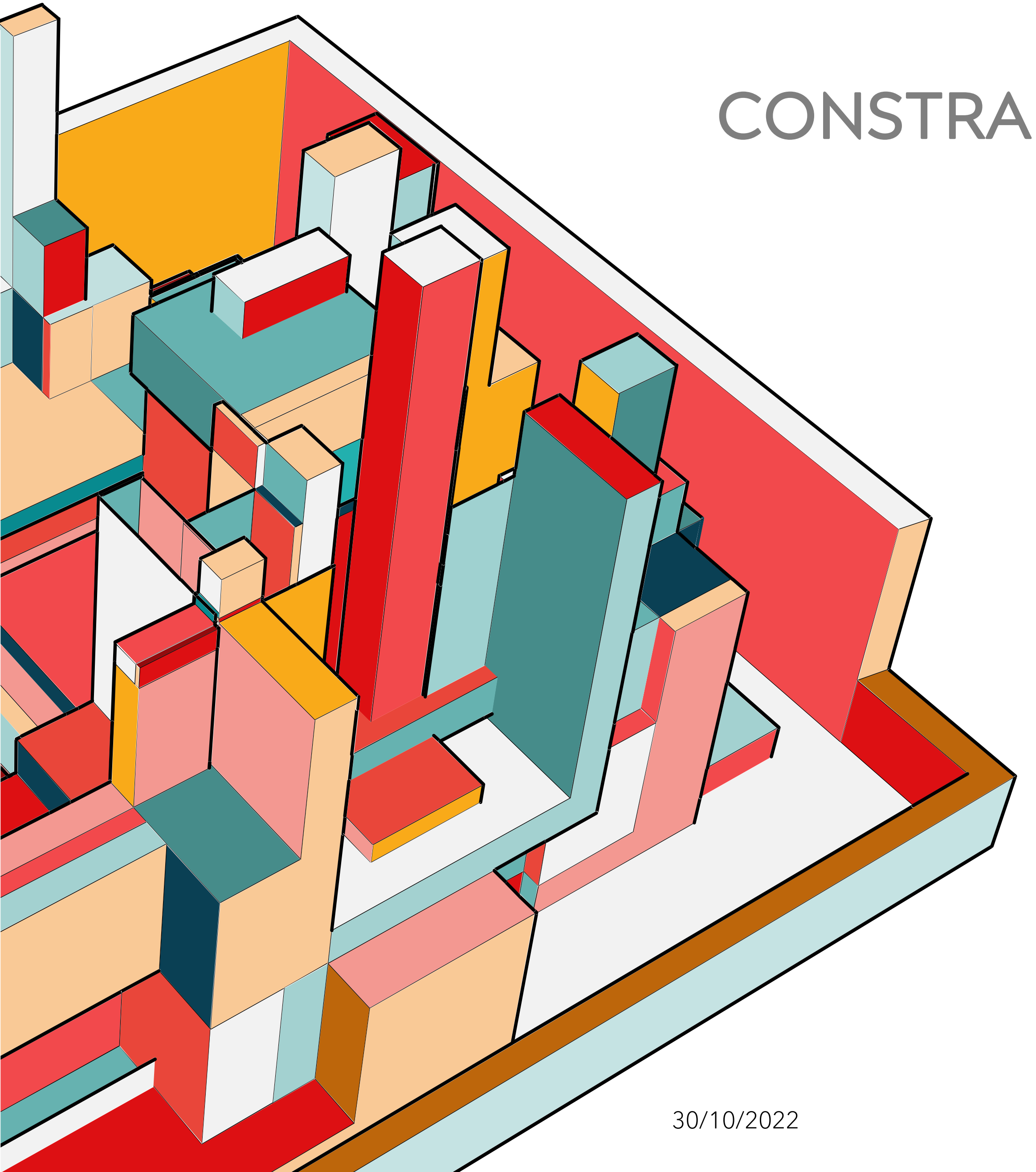
- Log files provided by the laboratory
- Classification methods spreadsheets



CRITERIA FOR SUCCESS

- Implement a Machine Learning algorithm able to detect at least 80% of malicious network flows
- Implementing a Malware Type Detector
- Having a deployable pipeline for malware detection in real-time setting





CONSTRAINS WITHIN SOLUTION SPACE

- Not getting enough computational power to analyze all log files.
- Malware information being outdated and not representative of how new malware works
- Class imbalance for the binary class or multi class project

KEY FINDINGS AND INSIGHTS

Binary classification project (Class 1-Malicious, Class 0-Benign) with a final dataset of:

380,000 observations

67 features

Key Features Enough for a One-Feature Model

Protocol
Origin Port
Port Used for Response
Network History
# of Bytes Sent to Host
# of Response Bytes
# of Response Packets

Constraints faced

Severe class imbalance for types of malware (8 classes)
Dataset only enough for binary classification

RAM power enough for analyzing 6 scenarios

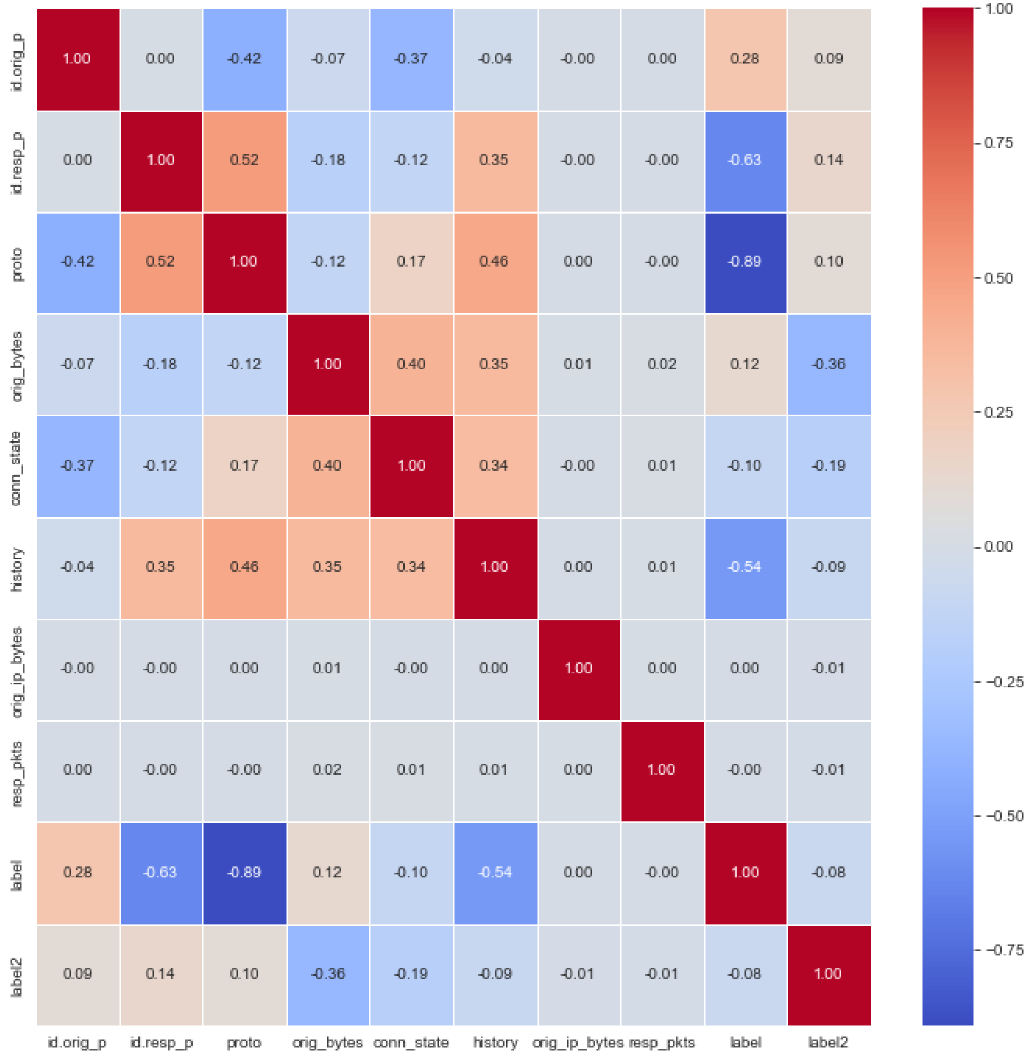
Insights

Data Distribution between classes very marked in some features

Time-related Features nor dimensionality reduction

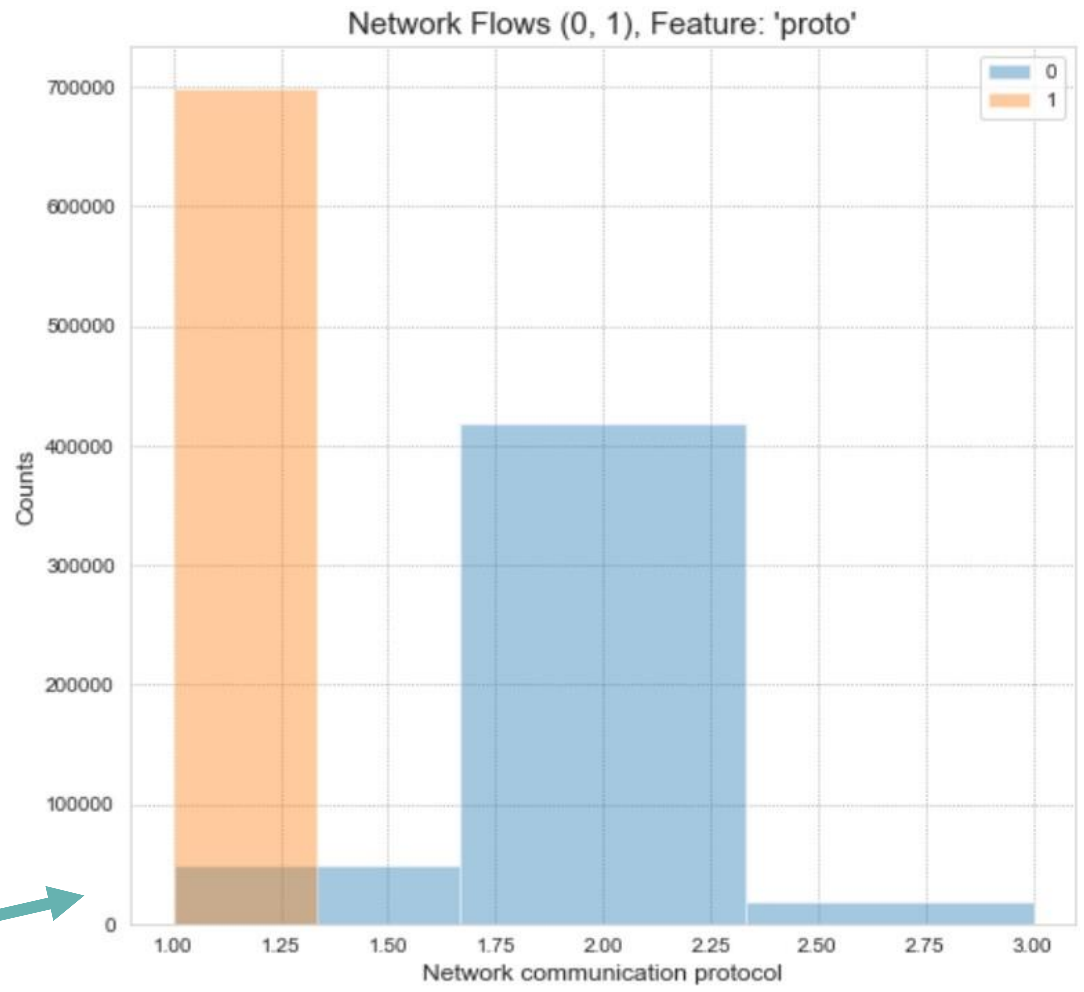
Key Features dropped to add complexity to the modeling

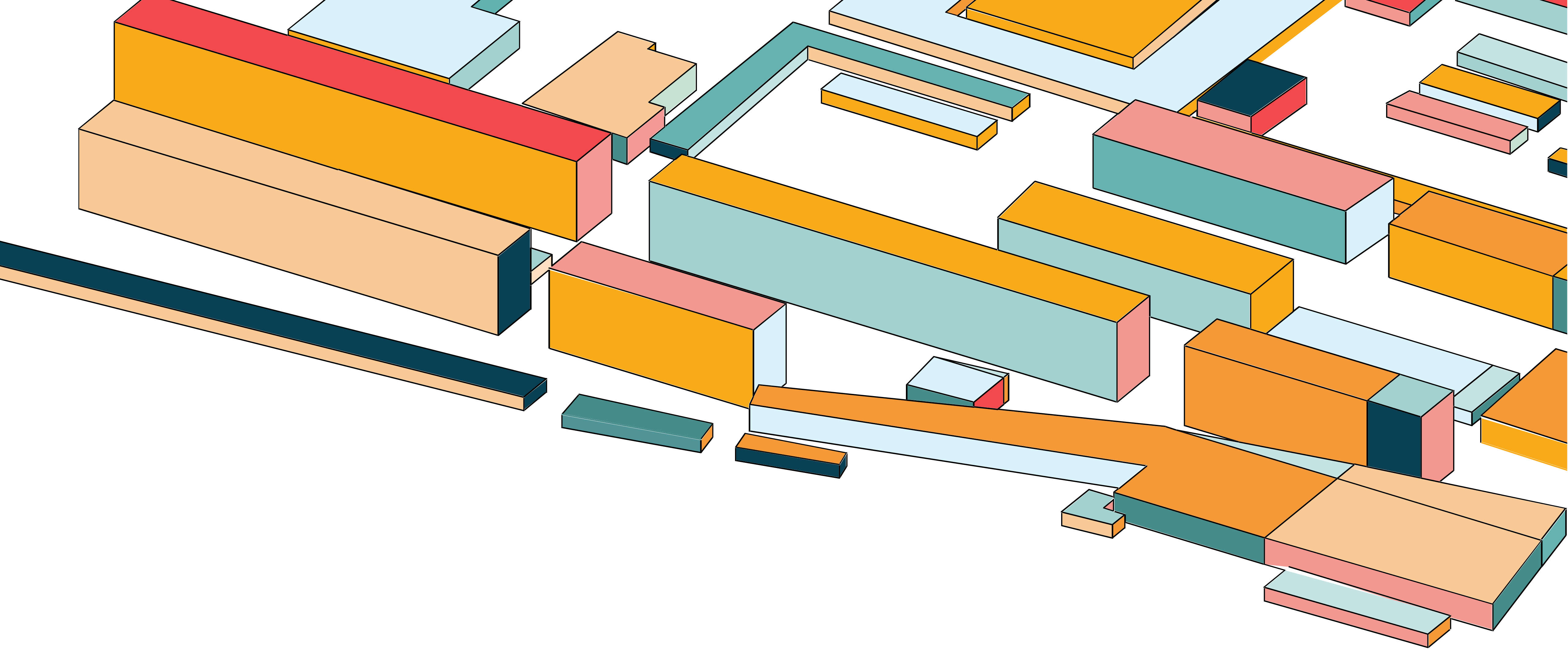
FEATURE HANDLING



Feature drop was based on:

- Collinearity
- Correlation with label 1
- Distribution differences between Classes (example of Protocol)





MODEL RESULTS AND ANALYSIS

"ONE-FEATURE" MODELS

Model	Feature	Precision	Recall
1	proto	0.89	1.0
2	id.orig_p	0.88	0.90
3	id.resp_p	0.90	0.92
4	History	0.90	0.93
5	orig_ip_bytes	0.88	1.0

* Features eventually dropped

Based on simple assumptions

Features showing high differences between classes were used

Example:

"All malicious network flows are using TCP protocol"

MODELS AND METRICS USED

METRICS COMPUTED PER MODEL

Classification Report
Precision
Recall
Support
Accuracy
ROC-AUC

METRICS PRIORITIZED FOR MODEL SELECTION

Precision (Class 1)
Recall (Class 1)

MODEL RESULTS

Model	Precision	Recall
Logistic Regression	0.84	0.90
KNN	0.76	0.87
Decision Tree	0.78	0.80
Random Forest	0.81	0.86
SVM	0.82	0.92
XGBoost	0.81	0.87

MODEL SELECTION AND TUNING

The model selected was:

Support Vector Machine

Considerations:

- Precision and Recall
- Computational time
- Overall performance

Parameters tuned and selected

(GridSearchCV)

- Scaler
- C
- coef0
- decision_function_shape
- degree
- gamma
- kernel
- probability.

SVM (Tuned) MODEL RESULTS

Precision:	0.84
Recall	0.90
F1 Score	0.87
Support	0.90
Accuracy	0.87
Best AUC Score	0.87

THANK YOU

Pablo Ruiz Lopez
+52 55-2729-6472
pabloweb8@gmail.com
https://github.com/pablo-git8