Network Intrusion Detection -

Classification of network traffic

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Background

With increasing cases of cyber attacks, it is important to identity irregular or abnormal network activities.

Medibank Becomes Latest Target of Cyber Attack in Australia

- Health insurer detected unusual activity on its network
- No evidence any sensitive, customer data was accessed

By Keira Wright
13 October 2022 at 09:58 GMT+8

Jonathan Greig
October 11, 2022

Government
Nation-state
News

Coverage of Killnet DDoS attacks plays into attackers' hands, experts say

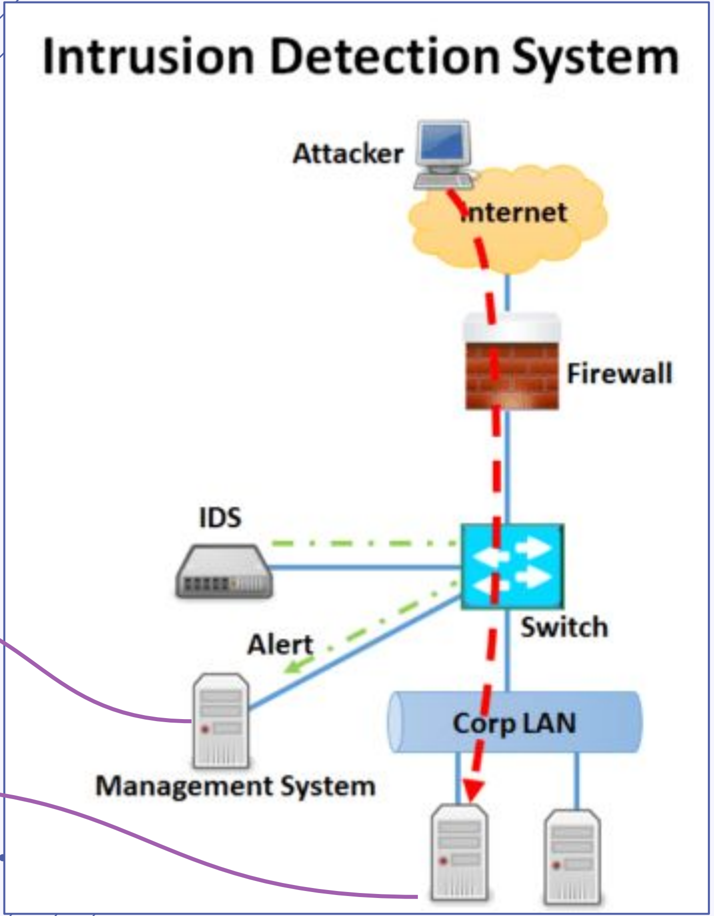
A notorious pro-Russian hacking group drew headlines on Monday after launching distributed denial-of-service (DDoS) attacks on the websites of airports in at least 24 different states and threatening more operations against U.S. entities.

Background

A network-based intrusion detection system (NIDS) is place to **collect** and **analyse** network traffic and **report** any behaviour that **falls outside normal activity**.

However, the known challenges of NIDS are

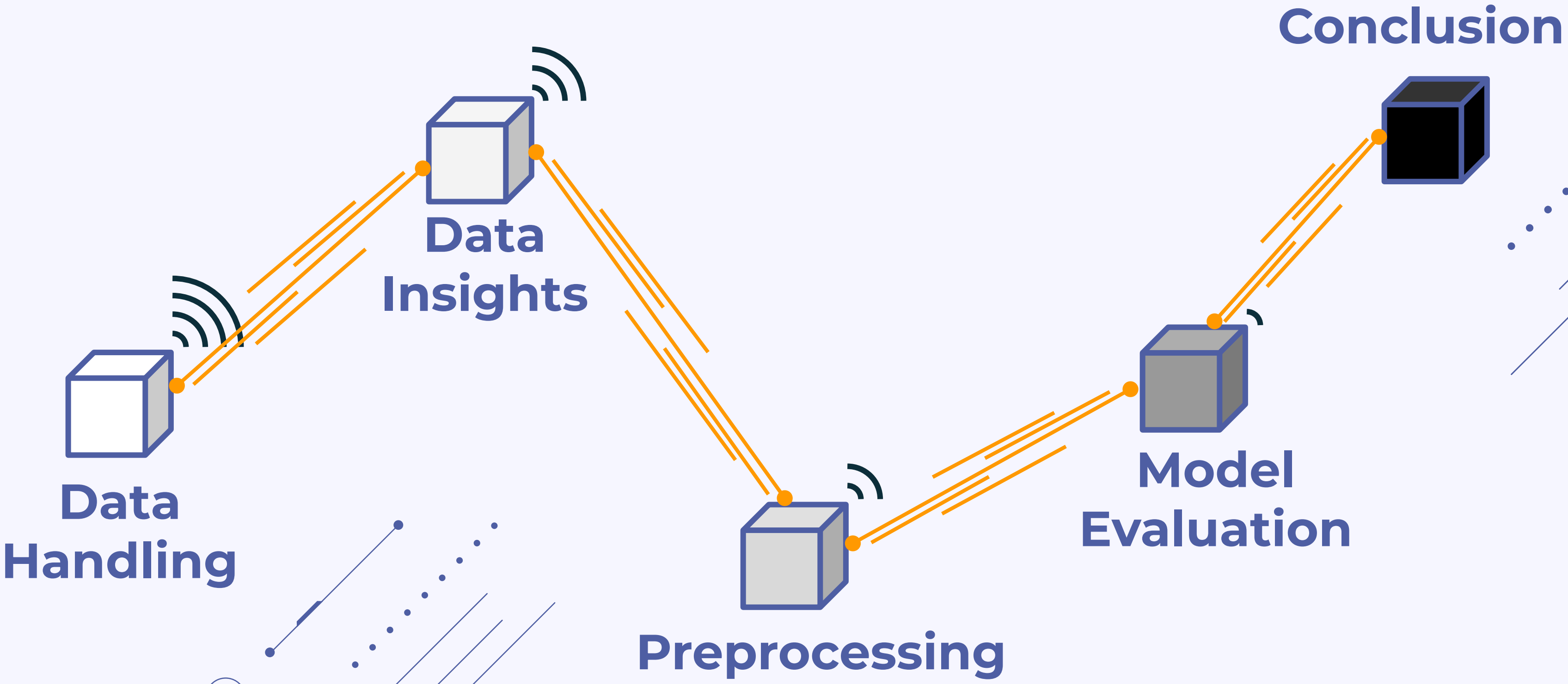
- High false alarm (*high false positive*) -> operation overhead
- Low detection rate (*high false negative*) -> prolonged attack go undetected



Problem Statement

1. Improve intrusion detection rate by **reducing false negatives**
2. Reduce operational overhead by **reducing false alarm rate**

Checkpoints



01

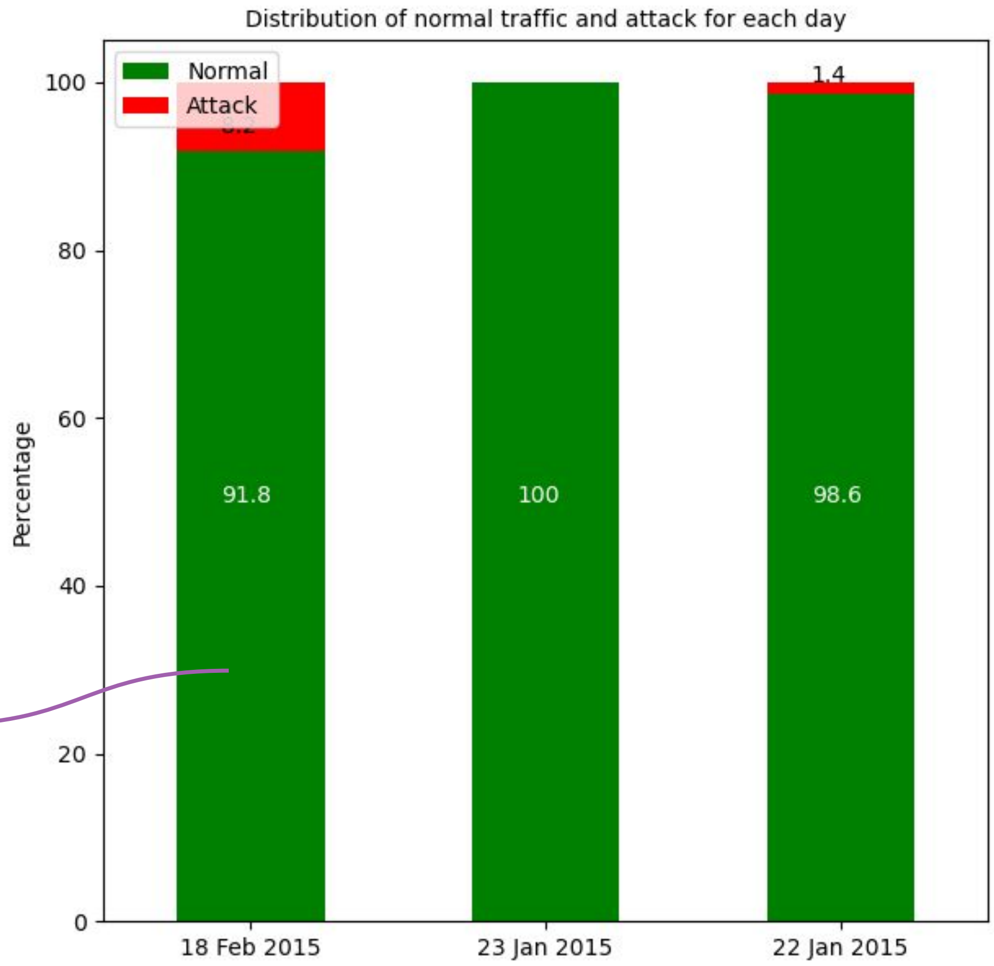
Data Handling

Dataset

(from University of New South Wales, Canberra, Australia)

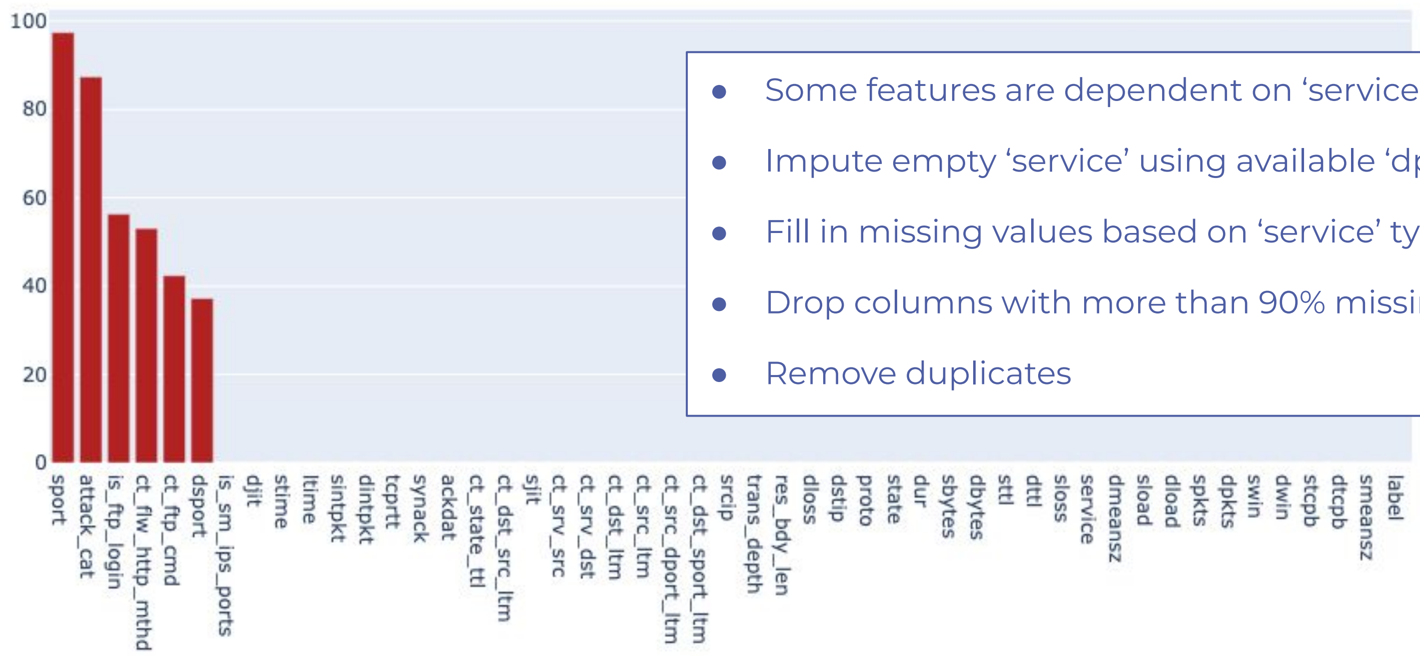
The dataset is made up of 2.5 million records consisting a hybrid of **real** modern **normal** activities and **synthetic** contemporary **attack** behaviours generated over 3 days.

Use a subset from 18 Feb 2015 due to the large dataset and is the least imbalance



Data Cleaning (based on best knowledge)

Percentage of missing values for each feature

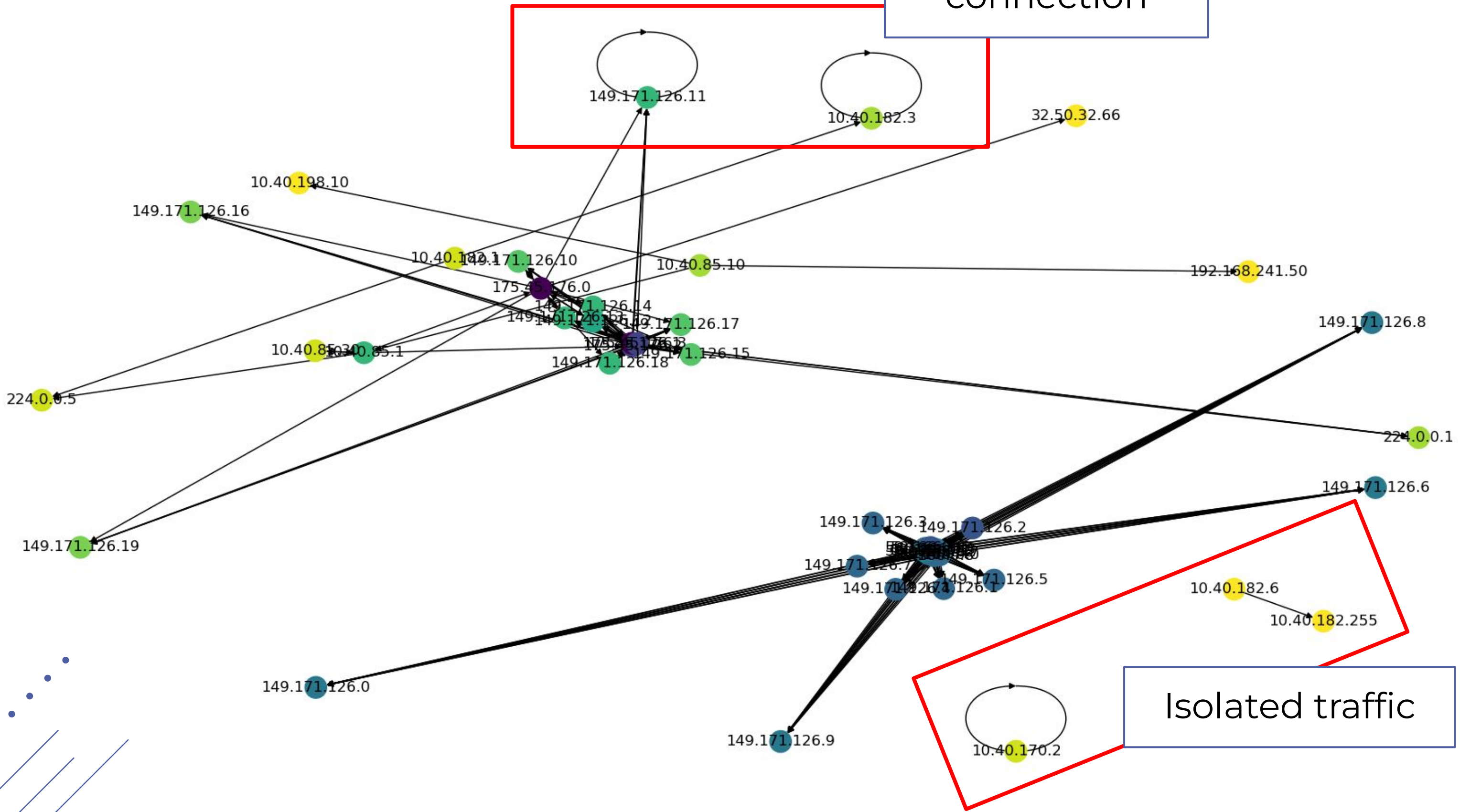


- Some features are dependent on ‘service’ type
- Impute empty ‘service’ using available ‘dport’ number
- Fill in missing values based on ‘service’ type
- Drop columns with more than 90% missing values
- Remove duplicates

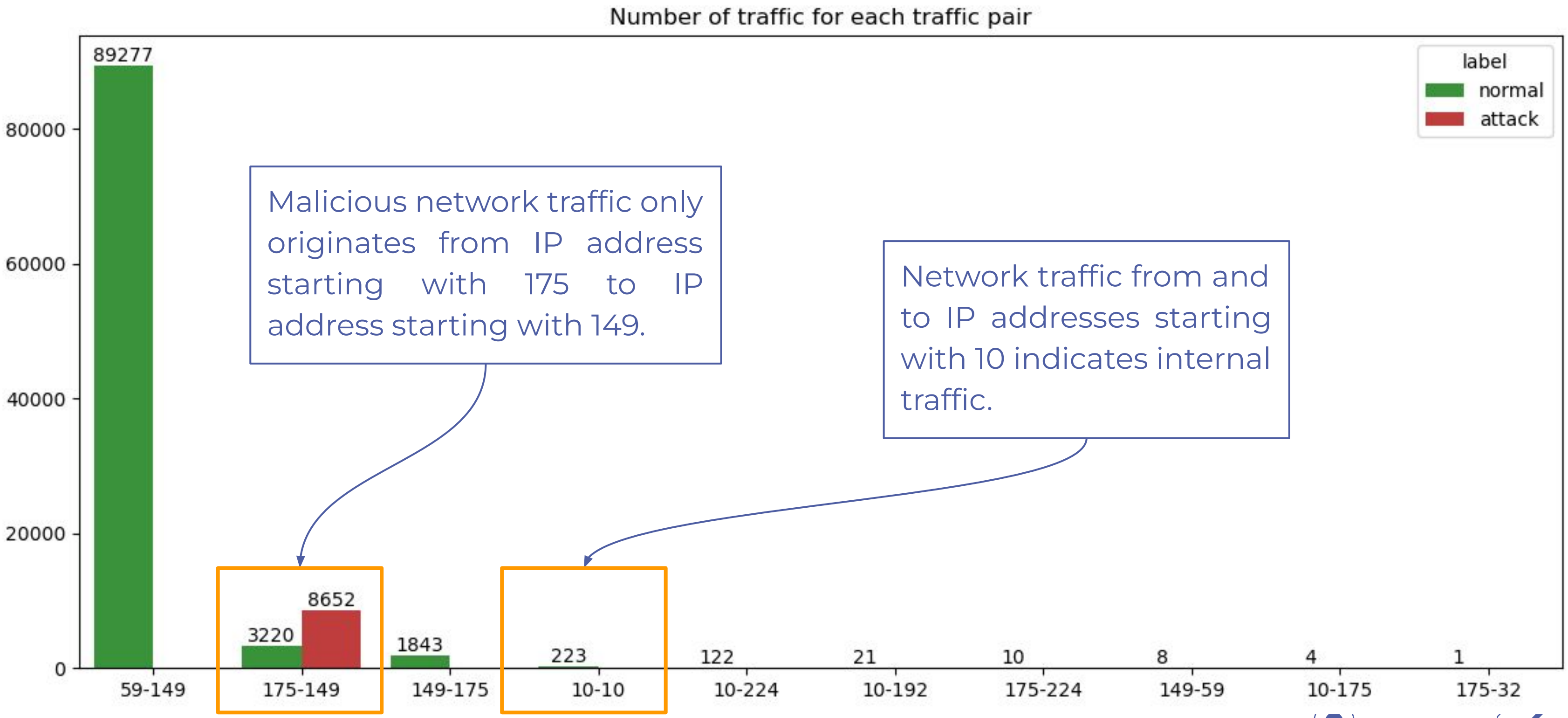
02

Data Insights

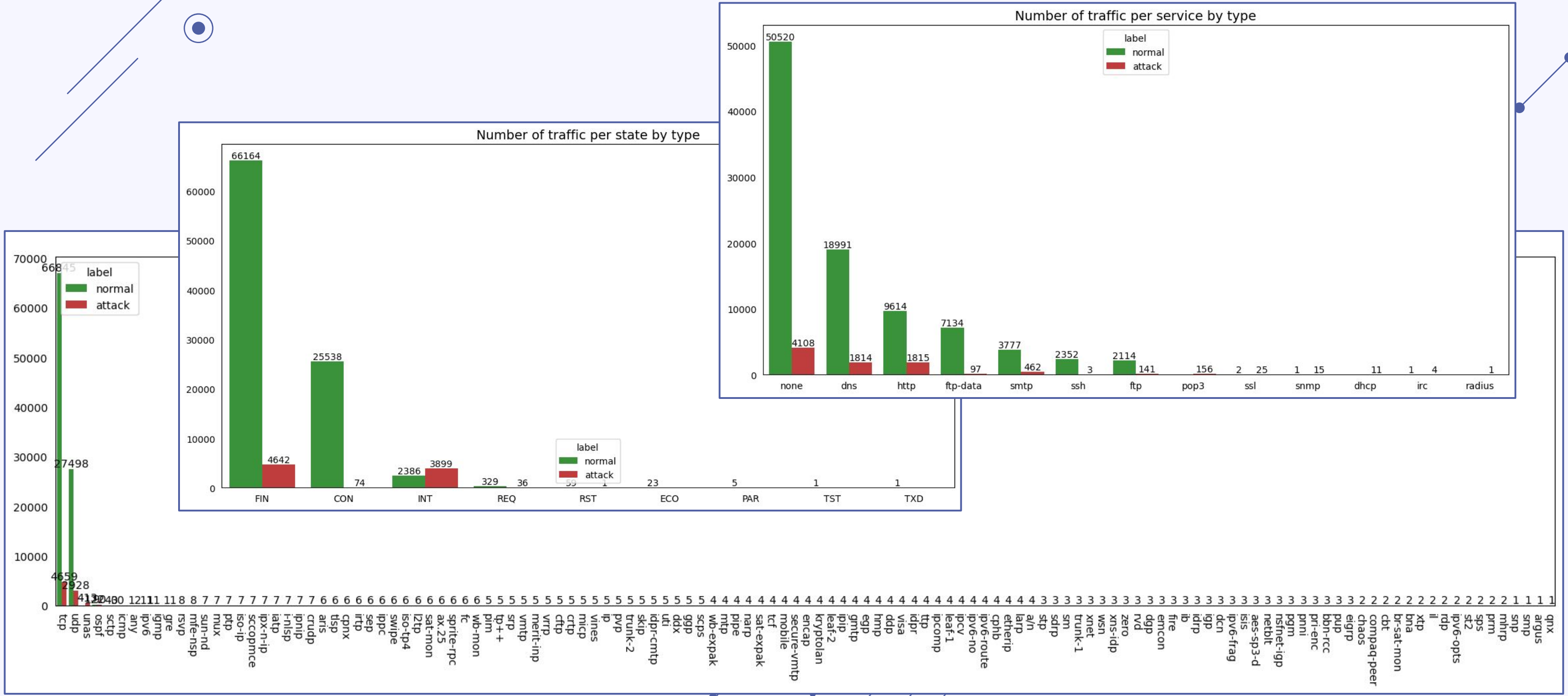
Traffic Behaviour



Traffic Pairs



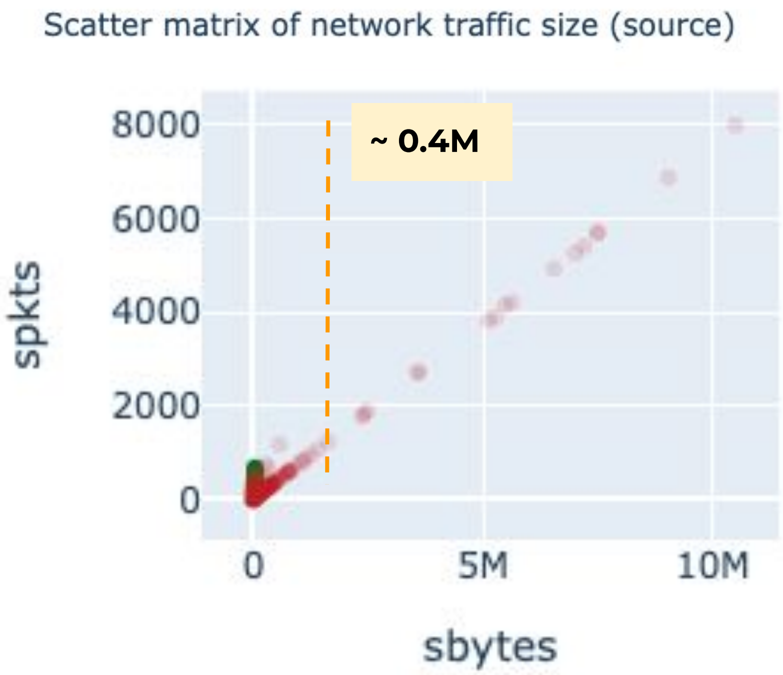
Protocol, State, Service

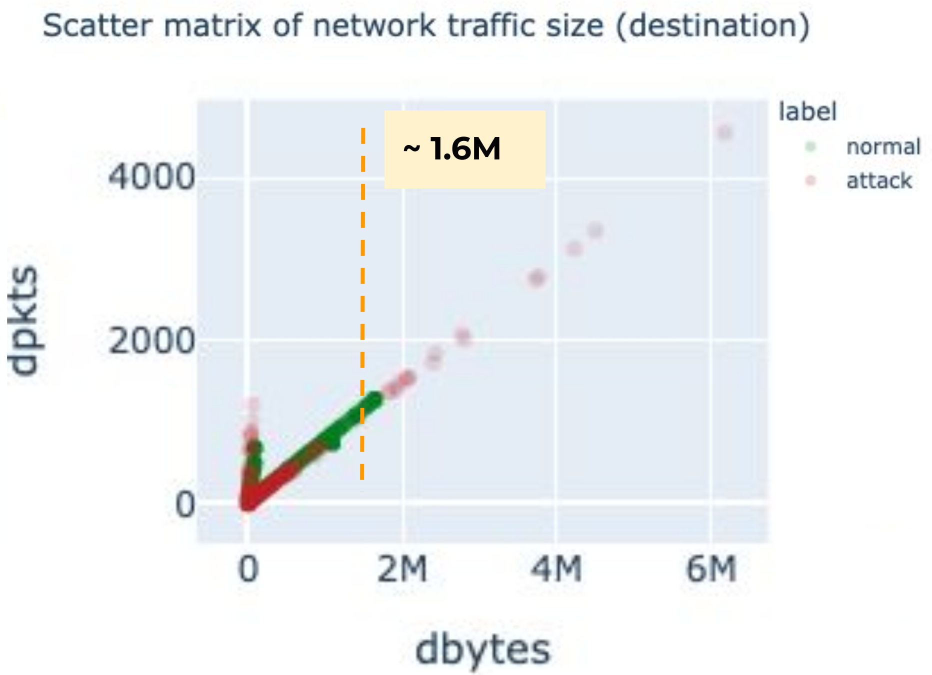


Protocol, State, Service

Transaction Size

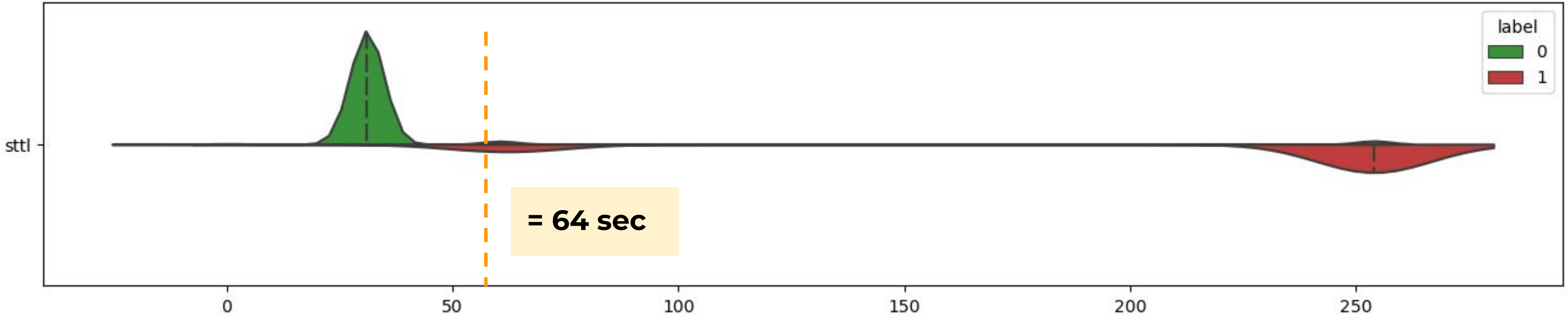
- Very strong positive linear relationship
- Attack tend to have larger transaction size for source and destination

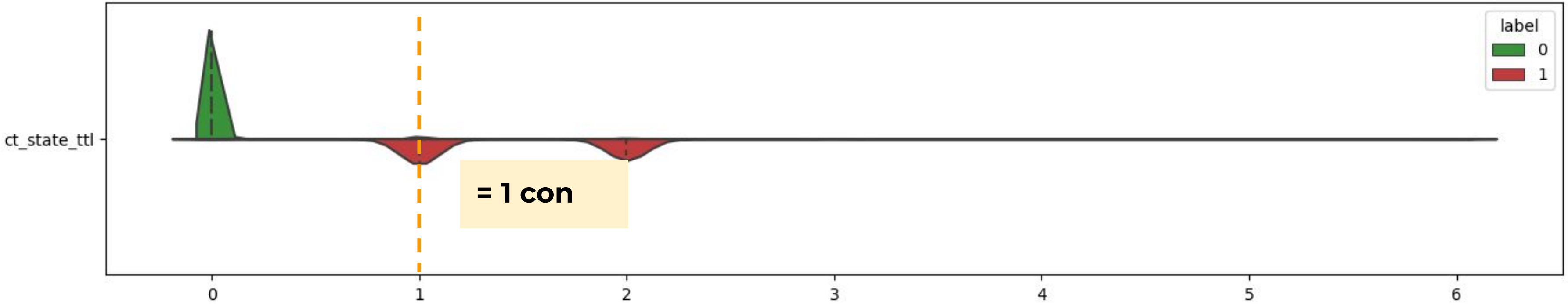




Time to live value

- Attack packets generally exist in network for a longer period before being discarded

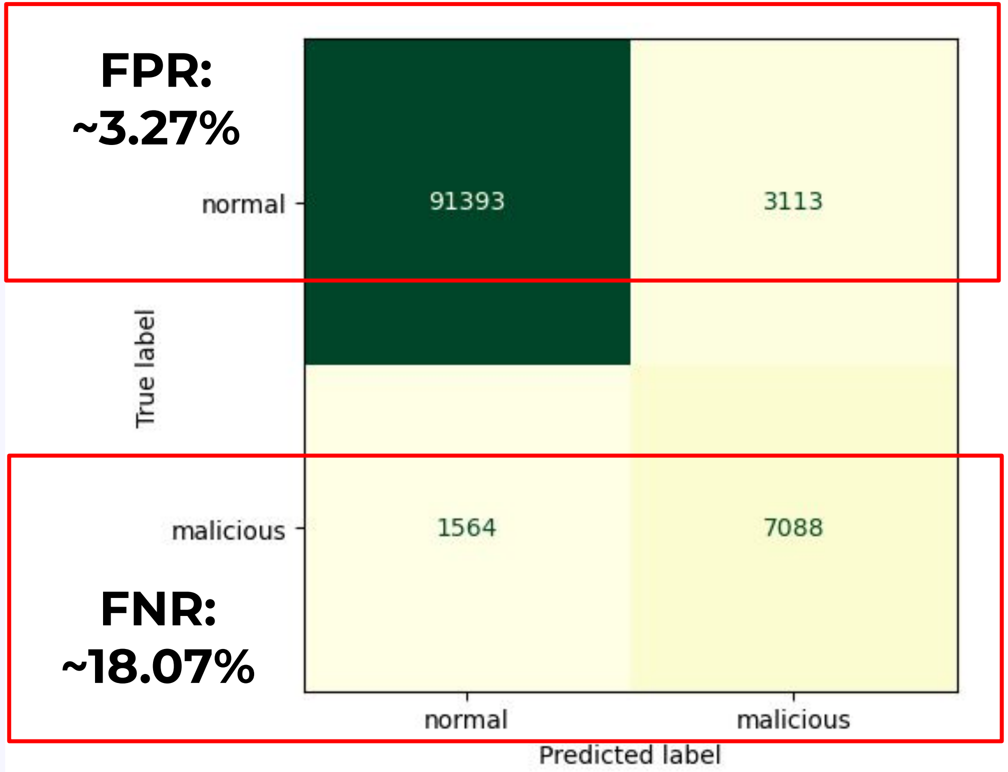




Baseline (rule-based filtering)

Classify traffic as attack using the following conditions:

- **dbytes > 1641360**
- **sbytes > 407794**
- **sttl > 64**
- **ct_state_ttl > 1**
- **service == other**
- **protocol == other**



03

Preprocessing

Preprocessing

Multicollinearity

- Remove highly correlated features using VIF

Prevent data leakages

- Remove IP addresses and attack types to prevent model from self-classifying

Preprocessing

- One-hot encode categorical features (service, protocol, state)
- Apply MinMaxScaler() since the value spread is wide for most of the features

Severely imbalance data

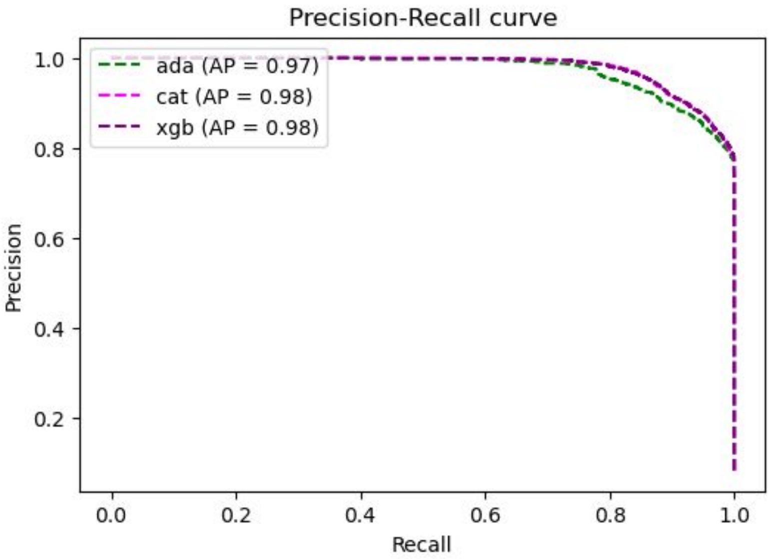
- Use algorithms that take care of class-weights

04

Model Evaluation

Model Evaluation

	model	time	train_f1	test_f1	gen_f1	train_precision	test_precision	train_recall	test_recall
0	ada	10min 19s	0.902	0.901	0.111	0.880	0.878	0.926	0.924
1	cat	7min 11s	0.919	0.893	2.829	0.850	0.816	1.000	0.985
2	xgb	9min 47s	0.921	0.908	1.412	0.932	0.914	0.910	0.903



- F1 scores are quite similar
- Generalise well
- Catboost model has the highest recall score and also runs the fastest

Problem Statement

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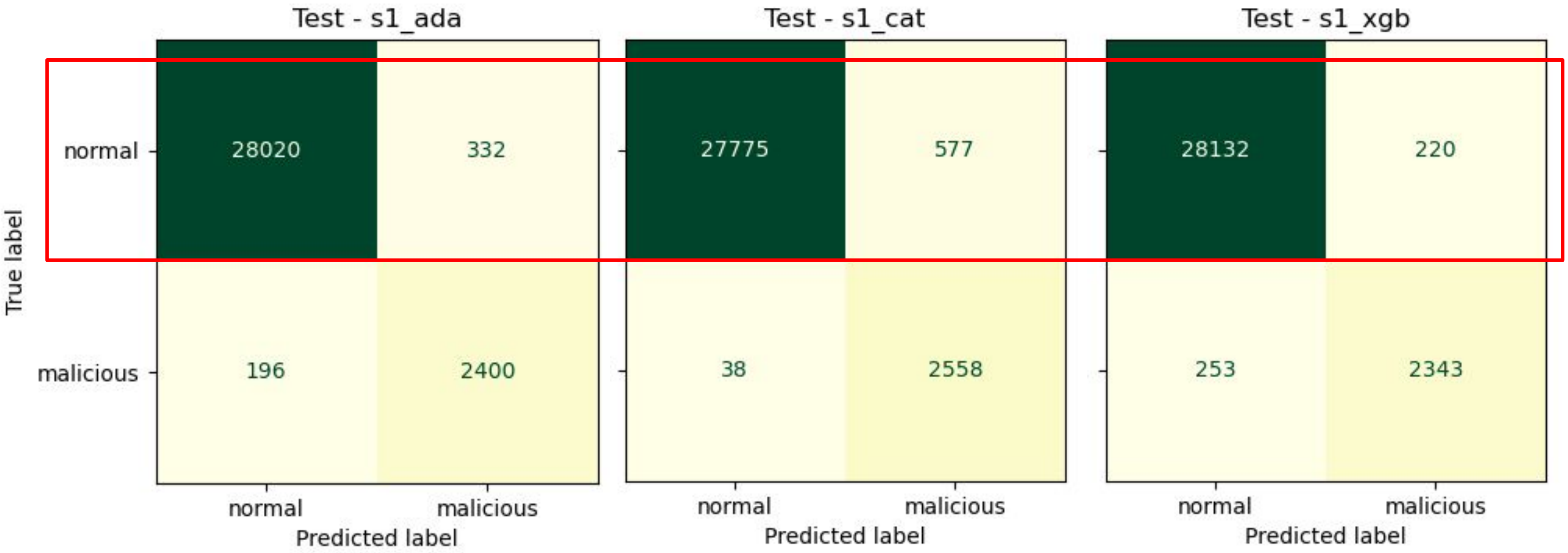
False Negative Rate

Model	AdaBoost	CatBoost	XGBoost
FNR	7.55%	1.46%	9.75%

False Positive Rate

Model	AdaBoost	CatBoost	XGBoost
FPR	1.17%	2.04%	0.78%



Test Set

Previously.....

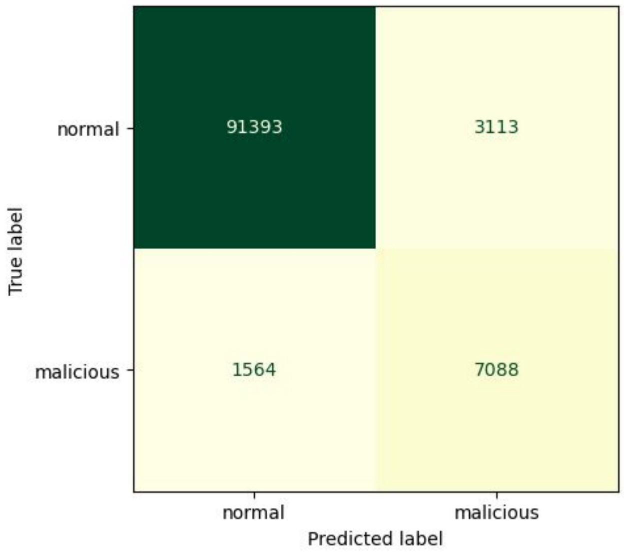
- Subset (10%) of 18 Feb 15 data was used to identify best model
- Remaining data (90%) is unseen to simulate production data

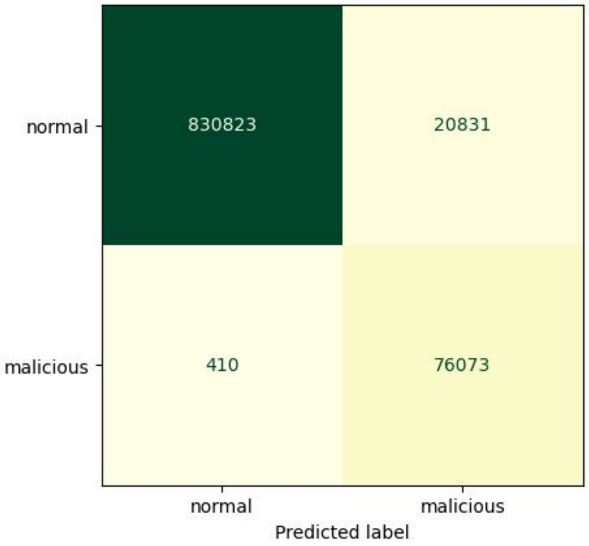
Predict

Fit the model on the train data (without train_test_split)

Test Set

	Without Model	With CatBoost Model	Improvement
FNR	18.07%	0.54%	- 17.53%
FPR	3.27%	2.45%	- 0.82%





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Conclusion

Future Improvements

The results are very positive for a severely imbalanced dataset. This could be due to the lack of variation in the malicious network traffic.

- Use dataset with **more variety** as attacks would not originate from or target specific IP addresses in real life cases.
- Use dataset with a **longer time period** to train the model for better representation.
- Consider **time series split** and check if model generalises well with future data.

Thank You

Special thanks to
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