Malicious traffic detection using Machine Learning

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Outline

- Introduction
- Proposed approach
 - Dataset collection and labelling
 - Online evaluation
- Conclusions

Introduction

Task

Task

The task is to detect malware traffic

What is malware?

Avast definition

Malware is an umbrella term for any type of "malicious software" that's designed to infiltrate your device without your knowledge, cause damage or disruption to your system, or steal data. Adware, spyware, viruses, botnets, trojans, worms, rootkits, and ransomware all fall under the definition of malware^a

Kaspersky definition

Malware is malicious software that is purposefully designed to cause harm to you or your device.^a



^ahttps://www.avast.com/c-malware

^ahttps://www.kaspersky.com/resource-center/threats/malware-protection

Malware types

RANSOMWARE



Blackmails you

SPYWARE



Steals your data

ADWARE



Spams you with ads

Types of Malware

WORMS



Spread across computers

TROJANS



Sneak malware onto your PC

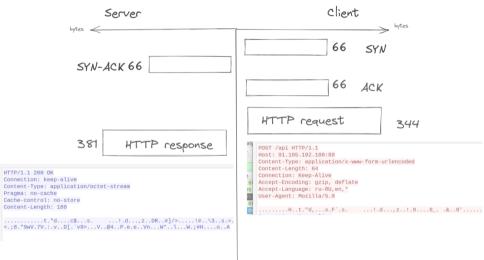
BOTNETS



Turn your PC into a zombie

1

What is traffic?

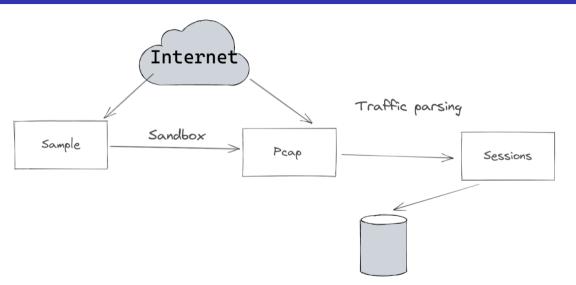


Definitions

Objects

- Sample is an executable file (*.exe, *.so, *.dll)
- Samples network activity can be saved in pcap file
- Session is a network activity between two IPs

General data flow pipeline



Static analysis

- Static analysis
- Dynamic analysis

- Static analysis
- Dynamic analysis
- Network traffic analysis[1]

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 - Port based

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- Static analysis
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 - Port based
 - DPI based
 - Statistics based
 - Behaviour based, e.g. to identify application (web-server)

ML based approaches

- Flow based
- Hybrd (aggregate static, dynamic, behaviour approaches)

Pros and cons for rule based approach

Pros

- Direct solving
- No ML magic, explainable
- High precision

Cons

- Time to market is very slow
- Constantly needs an infosec expert for rule writing
- Poor recall

Pros and cons for ML based approach

Pros

- Time to market is rather fast
- Ideally needs a ML expert only once
- High recall and high precision
- Can detect zero-days*
- Process encrypted traffic*

Cons

- Needs data
- Some ML magic, has issues with explainability
- Needs some feature engineering
- We will always have FP

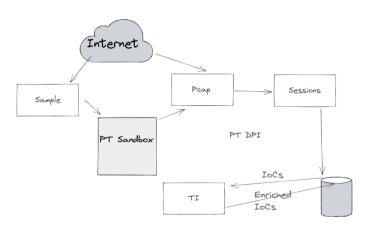
Proposed approach

ML task

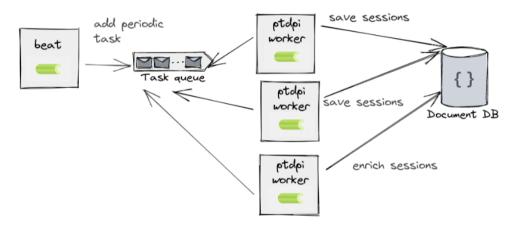
Objects & labels

- Binary classification task: benign vs malicious
- Object is a tcp session
- Label can be taken from behaviour, static analysis for either sample or pcap

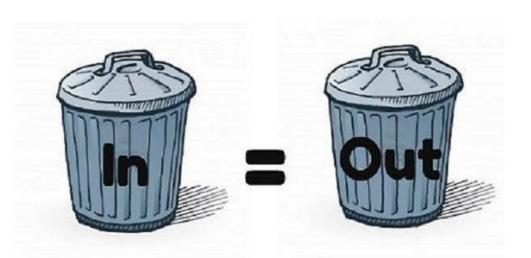
Dataset collection



Dataset collection. Detailed



Dataset labelling. Garbage in, garbage out



Each pcap can contain benign or malicious sessions

• Based on whole pcap label

- Based on whole pcap label
- Based on Threat Intelligence (malware hosting problem)

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 - Some ips are present only for a particular family (CnC).
 - Some ips are present for nearly every family (8.8.8.8). High idf

Data

Stats

- \geq 700k pcaps. Daily $+ \sim 5k$ pcaps
- > 5kk sessions
- \geq 150 not normalized family names (rat/redline vs trojan/rat/redline)

Features

Tcplen features

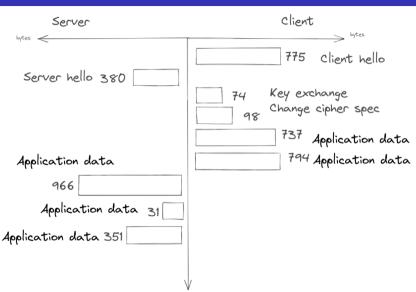
- Fixed size vector of tcp payload length in bytes. Max vector size is 30 (configurable)
- Contains packet direction: to server, to client

Pros of simple features

- fast feature calculation (stream processing)
- fast training
- fast inference



What is a tcplen vector?



Features

Aggregated tcplen features

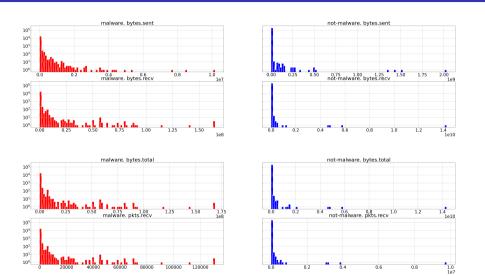
- Define: tcplen padded tcplen_stat array with zeroes, rcv array of bytes' lengths send to server,
 snd array of bytes' lengths send from server.
- Calculate min, max, mean, std, mode for snd, rcv, tcplen_raw
- Join bytes in groups based on max MTU

General features

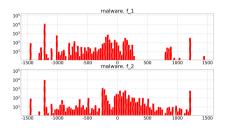
- Session duration in ms
- Bytes and packets send, recieved and total

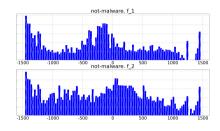


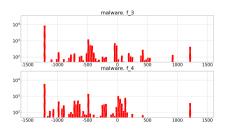
Features distribution

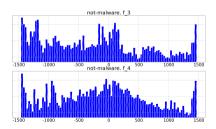


Features distribution

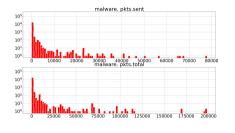




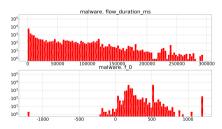


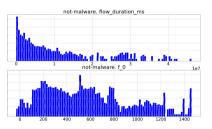


Features distribution

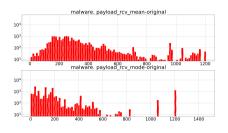


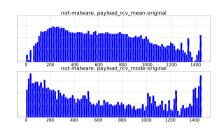


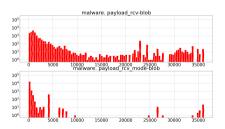


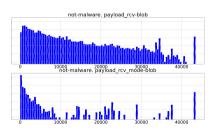


Features distribution









ML model



Gradient-boosting

LightGBM is a gradient boosting framework that uses tree based learning algorithms

Evaluation

Offline

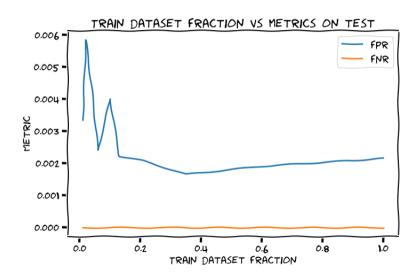
- Perform stratified K-fold cross-validation on base dataset. Save offline metrics to mlflow
- Calculate permutation importance
- Select best features
- Tune model hyper-params
- Test best n models on future data (4–5 days). Save metrics to mlflow
- Get the best model

Online

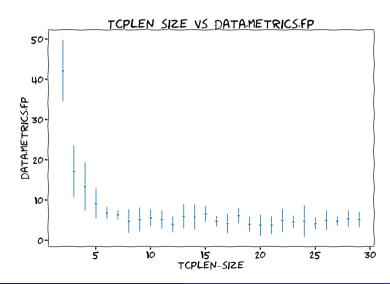
- Connect some best models to NAD's broker
- Analyze FP per day in grafana



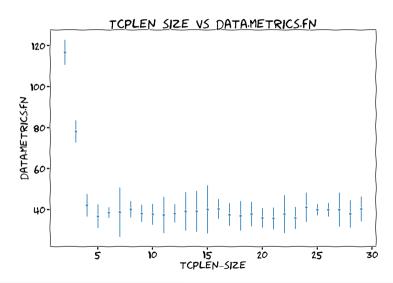
How much data do we need?



How many packets do we need?



How many packets do we need?



How many fp per day do we have?

FPR vs FP

- Network consits of ≥ 1.5 k hosts $+ \sim 15$ k servers, vm
- ullet Daily \sim 30kk sessions

FP	FPR
10	0.9999666

Conclusions

Main achievements

- ullet Can detect some malware families (\sim 5) with low fpr and high precision
- ullet The use of simple features o better perfomance
- Proposed approach is general. Can be applied not only for malware detection

Perspective

To do

- perform more experiments on recall analysis. New malware family detection
- integrate into NAD
- creatre a fully automated pipeline (no need for infosec expert)

References I



E. W. Biersack, C. Callegari, and M. Matijasevic. Data traffic monitoring and analysis. In *Lecture Notes in Computer Science*, 2013.