

nmap-harvester

A supervised machine learning model designed for detecting NMAP port scanning, developed as part of a university project.

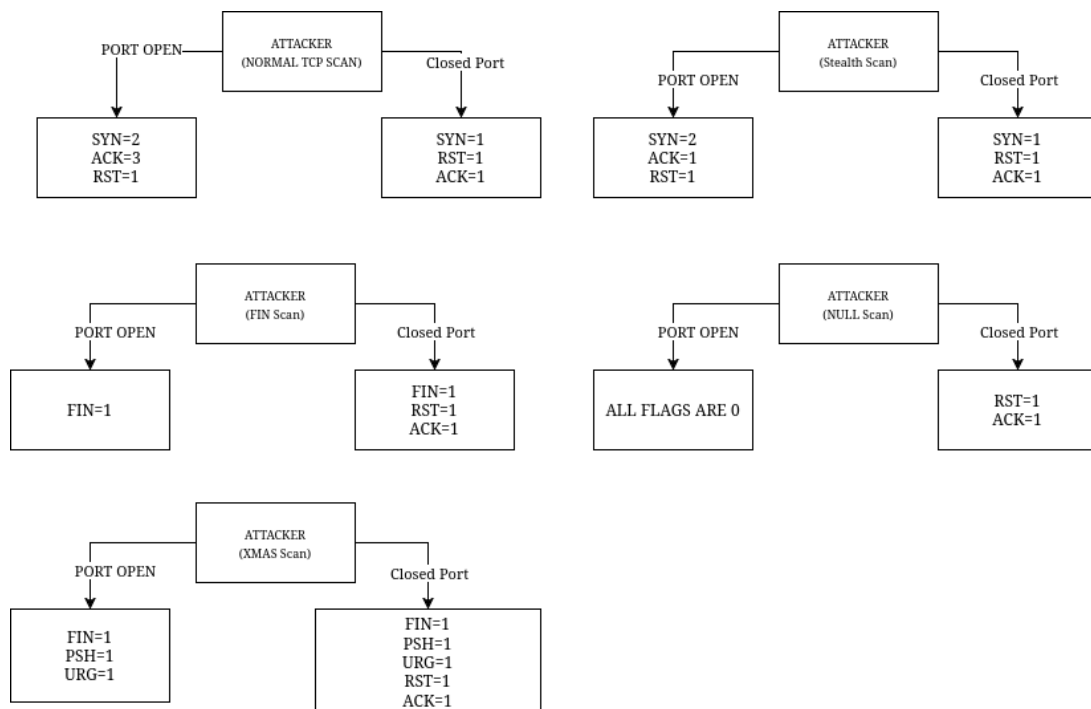
Introduction

This project aims to build a supervised machine learning model to detect real-time NMAP port scanning activities.

In many cyber-attacks, the initial step often involves port scanning using tools like NMAP . Detecting such scans can be challenging because network packets carry extensive information, and a single packet isn't enough to confirm an NMAP scan attempt.

To address this, this project proposes a machine learning-based approach for identifying TCP port scans initiated by NMAP .

How the interceptor.py collects all TCP flags can be summed up in the following scheme.



All this attack data are collected by the `interceptor.py` which listens for coming connection on a specific ip address.

In the project the following files have the described functions:

- `interceptor.py` -> monitor for collecting data
- `algo_chooser.py` -> script for choosing the best machine learning algorithm
- `injector.py` -> injects nmap scans or run normal http requests
- `classifiers.py` -> define a big list of classifiers for `algo_chooser.py`
- `noiser.py` -> helper script for sending normal http requests
- `detector.py` -> runs a real-time demo of the model using previously mentioned scripts internally
- `export_model.py` -> utility for model exportation
- `model` directory -> contains exported model

- `merger.py` -> merges 2 datasets in one single dataset
- `datasets/delayed/merged.csv` -> contains just another dataset for calculating accuracy and other stats
- `datasets/train/merged.csv` -> contains the datasets used for training the model
- `datasets/runtime` -> contains generated runtime datasets when running `detector.py`

The entire software is designed for running on a Linux environment and although the only changes needed for running on another operating system are interface names, some checks may fail due to different environments.

For example: `detector.py` (<https://github.com/Virgula0/nmap-harvester/blob/main/detector.py#L55>) contains a check to run with `root` privileges and this check should be commented if the environment is different from Unix.

This disclaimer has been inserted because I noticed the usage of other operating systems during the course lectures. Running the `detector.py` on a virtual environment should work because everything is set to run on the `localhost` interface, but even here, the creation of the dataset phases may not work because of interfaces used by pyshark on a virtual machine. A solution can be to create another container and let the 2 isolated container to communicate between them, but this is up to the readers to investigate better eventually.

Requirements

Install dependencies with:

```
python3.11 -m venv venv && \ # python3.13 has been tested to have some problems
when trying to install catboost
source venv/bin/activate && \
pip install -r requirements.txt
```

`cargo` (rust) may be needed for `catboost` ML model.

Use this script to install it `curl --proto 'https' --tlsv1.2 -sSf https://sh.rustup.rs | sh` (Use default settings)

Train Dataset Creation `datasets/train/merged.csv`

Understanding TCP connections is important for building the dataset. When a TCP packet is sent over the network, it carries specific flags that facilitate the 3-Way Handshake. NMAP can manipulate these flags to evade detection while performing rapid port scans. We cannot create a dataset where each row of the dataset represents a packet since for detecting NMAP, multiple packets are needed, so the idea:

Key Dataset Characteristics

- **Session-Based Rows:** Instead of logging each packet individually, each row in the dataset represents a **session** (requests + responses).
- **Flag Summation:** Flags (SYN, ACK, FIN, etc.) are aggregated across the same session. For example:
 - If a SYN packet is sent by NMAP and another SYN is sent by the host in the response (whatever the port is closed or opened), the SYN column will record a value of 2 because of their sum.
 - The dataset contains 6 (SYN, ACK, RST, FIN, URG, PSH) out of 9 TCP flags. NMAP uses those flags, but in the case of other new attacks, the dataset can be rebuilt using other TCP flags, too.
- **Duration feature:** `start_response_time`, and `end_response_time` will be set to 0 if only a packet has been found in the entire session. In this case, the duration will be only `end_request_time - start_request_time` otherwise the session duration is `end_response_time - start_request_time`

Example Dataset Row (normal tcp scan on a closed port 22)

```
2025-01-15 12:49:08.025898,2025-01-15 12:49:08.025898,2025-01-15
12:49:08.025946,2025-01-15 12:49:08.025946,4.8e-05,"['172.31.0.2',
'172.31.0.1']","['172.31.0.2', '172.31.0.1']","['52666',
'22']","['52666', '22']",1,1,0,1,0,0,1
```

- Sessions are grouped using `src_port`, and `dst_port` tuple as keys. However, these grouping keys are excluded and not necessary from the model's training phase.
- The `duration` feature provides valuable information for distinguishing between legitimate traffic and NMAP scans, as legitimate HTTP requests may exhibit similar flag behaviour but differ in timing.
- The session window in `interceptor.py` is set to **0.5 seconds** by default, as this is typically enough to capture an NMAP scan attempt on a single port.

More technical explanations are present via comments in `interceptor.py`. The script takes a while for writing successfully all the data when a lot of requests are performed.

During the data collection, some ports were opened intentionally on the host to differentiate some rows in the dataset. For example, an HTTP server on port 1234 has been opened using the following method:
`python3 -m http.server 1234` plus, eventually other ports that had already been opened from other services between the range 0-5000.

Common NMAP Scans

The following commands were run from the container called `traffic_generator` (the container) having the `sudo python3 interceptor.py` running locally.

```
nmap -sT 172.31.0.1 -p 0-2500 # TCP Scan
nmap -sS 172.31.0.1 -p 0-2500 # Stealth Scan
nmap -sF 172.31.0.1 -p 0-2500 # FIN Scan
nmap -sN 172.31.0.1 -p 0-2500 # NULL Scan
nmap -sX 172.31.0.1 -p 0-2500 # XMAS Scan
```

The result is the creation of `bad.csv`

Then the script `noiser.py` was used for generating `good.csv`

The final dataset consists of a merge (`merged.csv`) used for training the model:

- `bad.csv` : Sessions labelled as `1` (NMAP traffic).
- `good.csv` : Sessions labelled as `0` (legitimate traffic).

Machine Learning Model

The `XGBClassifier` was selected as the final model due to its reliable performance in key areas:

1. High accuracy score (`~0.99`)
2. Fast prediction speed (`~4ms` on average for `24.511` rows)
3. High MCC score (`~0.98`)

Why accuracy metric is important?

The dataset generated for training purposes contains a balanced example of normal/anomaly behaviours, half normal and half anomalies, which get shuffled during the dataset splitting phase. Thus, accuracy is an important statistic that can be considered in this case.

Why MCC is not that important?

MCC should normally be preferred when unbalanced datasets are present. This is not our case, but it is taken into account even if it has a minor weight in the final machine-learning model choice.

Why the prediction speed is so important?

The prediction speed played a significant role in choosing this model, as it allows efficient analysis of large volumes of network traffic in real-time. The `RandomForestClassifier` is pretty similar in accuracy (maybe even better sometimes), but it has a slower prediction time in average of ~23ms compared to ~4ms of `XGBClassifier`. Of course it's useless to underline that even if `DeepSVDD` predicts in 1ms, given it's low accuracy rate it cannot be even considered.

Model Performance

Dataset loaded with 24511 records.
Dataset preprocessed successfully.

Duration	SYN	ACK	FIN	RST	URG	PSH	Label
0.000048	1	1	0	1	0	0	1
0.000016	1	1	0	1	0	0	1
0.000015	1	1	0	1	0	0	1
0.000014	1	1	0	1	0	0	1
0.000015	1	1	0	1	0	0	1

Dataset split into training and testing sets.

`KNeighborsClassifier (n_estimators=N/A): Accuracy: 0.9910, Train time: 13ms, Prediction time: 271ms, MCC: 0.982114, TP: 1238, TN: 1192, FN: 18, FP: 4`

....

`RandomForestClassifier (n_estimators=210): Accuracy: 0.9902, Train time: 650ms, Prediction time: 23ms, MCC: 0.980464, TP: 1238, TN: 1190, FN: 18, FP: 6`

....

`XGBClassifier (n_estimators=210): Accuracy: 0.9910, Train time: 86ms, Prediction time: 4ms, MCC: 0.982114, TP: 1238, TN: 1192, FN: 18, FP: 4`

....

`DeepSVDD (n_estimators=N/A): Accuracy: 0.6970, Train time: 22739ms, Prediction time: 1ms, MCC: 0.492361, TP: 526, TN: 1183, FN: 730, FP: 13`

....

Best Classifier based on Accuracy
Classifier: `XGBClassifier`
`n_estimators: 210`
Accuracy Score: 0.9910

Best Classifier based on MCC
Classifier: XGBClassifier
n_estimators: 210
MCC Score: 0.982114

Best Classifier based on prediction time
Classifier: DeepSVDD
Time : 1.000000ms

How Training Dataset was created (detailed)

The training dataset, `datasets/train/merged.csv`, is generated using the following steps:

1. Create an isolated Docker environment for sending clean packets:

```
docker compose up --build -d
```

2. Access the container:

```
docker attach traffic_generator
```

or

```
docker exec -ti traffic_generator /bin/bash
```

3. Run the interceptor on the host from another terminal:

```
sudo python3 interceptor.py
```

◦ Before to run, adjust:

- interface : Docker network interface name
- scanner_ip : IP assigned to `traffic_generator`
- output_file : Output CSV file path
- label : 0 for legitimate traffic, 1 for NMAP scans

4. Run NMAP scans from the container:

```
nmap -sT 172.31.0.1 -p 0-2500  
nmap -sS 172.31.0.1 -p 0-2500  
nmap -sF 172.31.0.1 -p 0-2500  
nmap -sN 172.31.0.1 -p 0-2500  
nmap -sX 172.31.0.1 -p 0-2500
```

5. Run noise traffic for legitimate requests, from the container:

```
cd /tmp/temp  
python3 noiser.py
```

6. Merge datasets:

```
cd datasets  
python3 merger.py
```

7. Train the model:

```
python3 algo_chooser.py
```

Delayed Dataset (Making things harder)

A delayed dataset can be created by introducing delays between requests:

```
nmap -p 1-5000 --scan-delay 1s 172.31.0.1
```

You can also adjust the delay in legitimate requests by modifying `SLEEP_SECOND` in `noiser.py`.

With this dataset, the results are a little different and worse.

The reasons why this happens are the following:

1. Here we have a minor number of data since it takes some hours to construct this dataset.
2. We added a scan delay that introduces a second delay between each Nmap attempt.
3. The attack type used by Nmap using the above command is a Stealth Attack by default, so flags between HTTP normal requests and Stealth Attacks are practically the same, the only information affordable is the duration (the backup feature introduced for these situations, when distinguish anomaly/normal packets using flags is impossible).

Given this 3 points above, and relying only on duration feature in these kind of situation, an accuracy of ~90% seems quite reasonable.

We still continue to prefer `XGBClassifier` for the same reasons discussed for the train dataset.

Dataset loaded with 10000 records.

Dataset preprocessed successfully.

duration	SYN	ACK	FIN	RST	URG	PSH	label
0.000067	1	1	0	1	0	0	1
0.000051	1	1	0	1	0	0	1
0.000062	1	1	0	1	0	0	1
0.000037	1	1	0	1	0	0	1
0.000042	1	1	0	1	0	0	1

Dataset split into training and testing sets.

`RandomForestClassifier (n_estimators=210): Accuracy: 0.8940, Train time: 483ms, Prediction time: 20ms, MCC: 0.789968, TP: 436, TN: 458, FN: 70, FP: 36`

....

`XGBClassifier (n_estimators=210): Accuracy: 0.8940, Train time: 52ms, Prediction time: 4ms, MCC: 0.789968, TP: 436, TN: 458, FN: 70, FP: 36`

....

`DeepSVDD (n_estimators=N/A): Accuracy: 0.4833, Train time: 10273ms, Prediction time: 1ms, MCC: 0.270419, TP: 173, TN: 376, FN: 579, FP: 8`

Best Classifier based on Accuracy

Classifier: `KNeighborsClassifier`

`n_estimators: N/A`

Accuracy Score: 0.8990

Best Classifier based on MCC

Classifier: `KNeighborsClassifier`

`n_estimators: N/A`

MCC Score: 0.798304

Best Classifier based on prediction time

Classifier: DeepSVDD

Time : 1.000000ms

Running the Detector

The `detector.py` represents the live-demo for NMAP attacks detection.

To run the detector:

```
sudo python3 detector.py
```

- The detector uses `interceptor.py` to monitor session packets.
- `injector.py` simulates normal HTTP traffic with occasional NMAP scans (10% probability).
- If at least **30%** of session packets are flagged as anomalies, the system will detect an ongoing NMAP attack.

When running the script, a log file containing all events called `logs` is created in the main project directory.

When running the script, some other connections directed to localhost interface may be collected in the process.

Demonstration Video

<https://github.com/user-attachments/assets/f10773c6-742e-4394-913e-42beb0cc3683>

References

- [Medium Article on NMAP Detection using Wireshark](#)
 - [Unix Stack Exchange - Detecting NMAP Scans](#)
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External Dependencies

- `pyshark`