nmap-harvester

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

Introduction

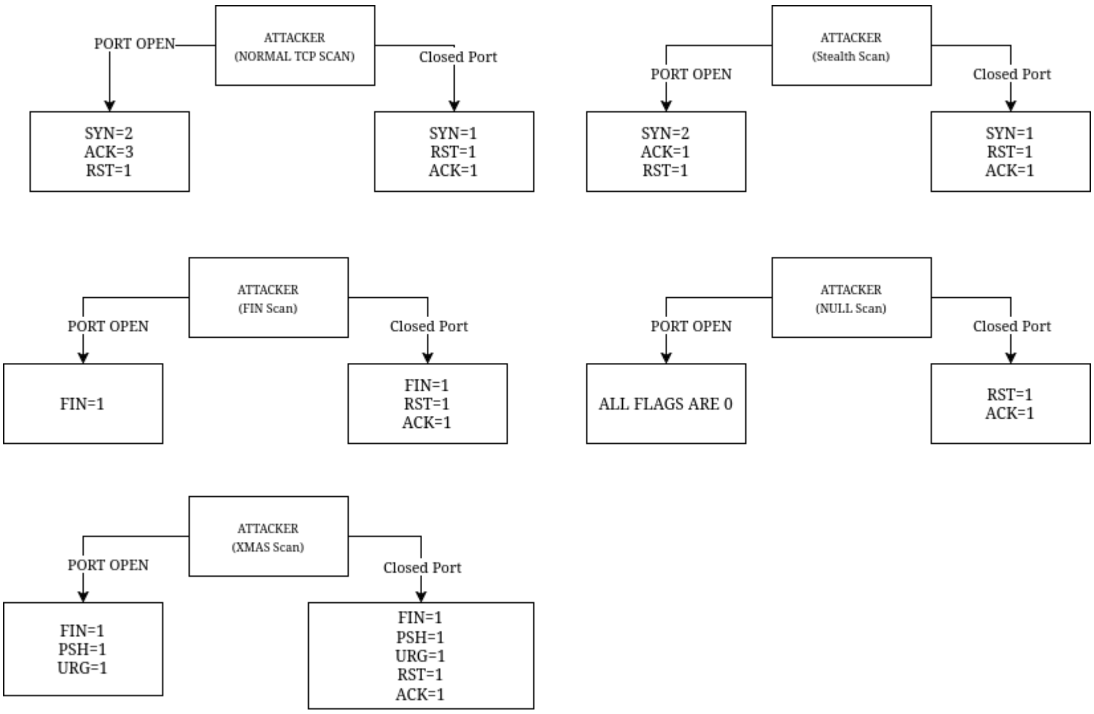
This project aims to build a supervised machine learning model to detect real-time `NMAP` port scanning activities.

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`.

The model will detect the following TCP attack types: `normal TCP scan`, `Stealth Scan`, `FIN Scan`, `NULL Scan`, `XMAS Scan`.

How the `interceptor.py` collects all TCP flags can be summered in the following scheme.



All this attack data are collected by the `interceptor.py` (monitor) 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`
- `dataset_and_train.py` -> create a dataset locally with bad and good data and produce a model trained on such data

- `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 however the only changes needed for running on another operating system are interface names.
>
> For example, windows does not have `lo` loopback interface, as well as ip addresses must be adapted.
>
> 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.

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 # this is full requirements for running algo_chooser.py too, if you want to skip it install requirements-minimal.txt instead
```

> `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`, `RST`, `URG`, `PSH`) 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 window 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)

```
start_request_time,end_request_time,start_response_time,end_respons
```

```
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, along with `src_ip` and `dst_ip` features, 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 succesfully 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 before to reach the training phase. Thus, accuracy is an important statistic metric that must 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 time played a significant role in choosing this model, as it allows efficient analysis of large volumes of network traffic in real-time at reasonable times. The `RandomForestClassifier` is pretty similar in accuracy (maybe even better sometimes for some millis), 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. The `XGBClassifier` uses an internally `gradient-boosted` (boosting) metalearner which in turn uses decision trees. The great optimization given by the meta-learner layer allows us to obtain a significant improvement in performances in the training and prediction phases maintaining the high accuracy score provided by the decision tree classifier.

Model Performance

```
Dataset loaded with 24511 records.
+------------+-----+-----+-----+-----+-----+-----+--------+
| 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     |
+------------+-----+-----+-----+-----+-----+-----+--------+
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. Choose the model:

   ```
   python3 algo_chooser.py
   ```

8. Train and export the model

   ```
   python3 export_model.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.
....
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. The host is required to having `nmap` and `tshark` (wireshark on windows) installed.

Depending on your distro

```
sudo apt update -y && sudo apt install nmap -y
sudo pacman && sudo pacman -S nmap
flatpak install nmap
```

You need to install `tshark` for `pyshark`

```
sudo apt update -y && sudo apt install tshark -y
sudo pacman && sudo pacman -S tshark
```

At this point you need at least minimal requirements (first define a virtual env)

```
pip install -r requirements-minimal.txt
```

> This is important. The `duration` feature is system depended and is calculated using time differentials on a given local system.
>
> Since on another system, duration feature can be slightly different because of pyshark times, the behaviour used in the pre-trained model (and so the live demo `detector.py`) can be affected by this.
>
> A solution is to re-create the training set again using `dataset_and_train.py` or alternatively using the train dataset creation procedure already described (more complex but more precise), and then, re-export the model by training it on new intercepted data.
>
> This is needed otherwise http normal request will be recognized as anomalies because of different duration times captured on another system.

Create dataset and train

```
sudo python3 dataset_and_train.py
```

> If you have processes running on localhost which may interfere with the capture and you notice that the `bad.csv` or `good.csv` monitor loop does not exist, you can force to continue by pressing ctrl+c. `bad.csv` and `good.csv` should have at least 12k data points per file.

```
sudo python3 detector.py
```

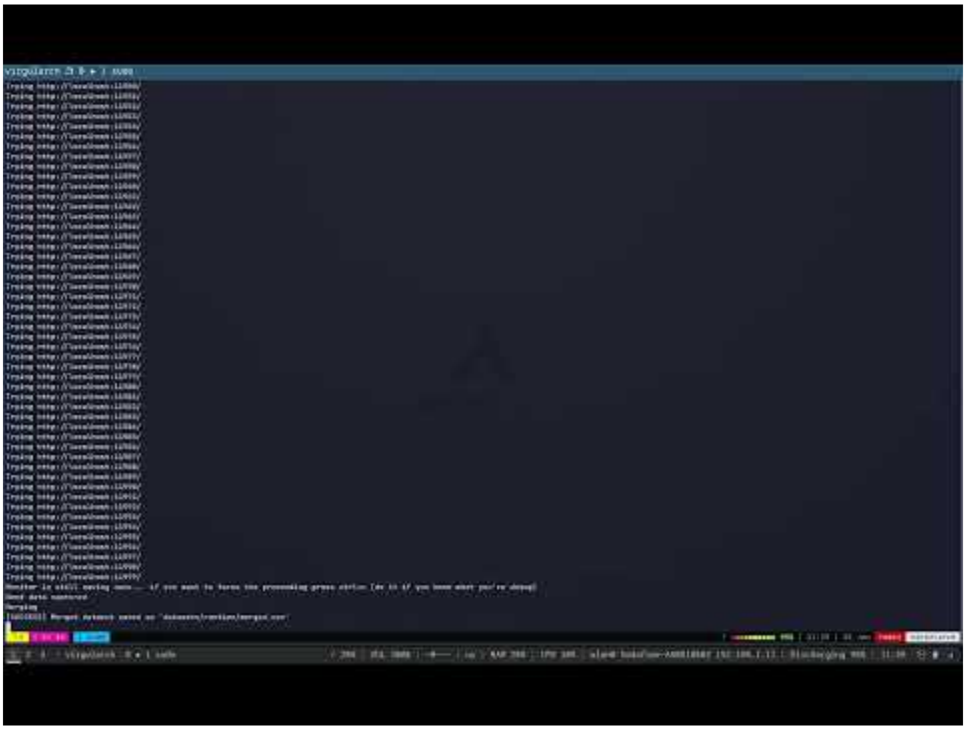
- The detector uses `interceptor.py` to monitor session packets.
- `injector.py` simulates normal HTTP traffic with occasional `NMAP` scans (10% probability).
- If at least **30%** of session packets are flagged as anomalies, the system will detect an ongoing `NMAP` attack.

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

> Some other connections directed to localhost interface may be callected in the process. Actually this gives a real scenario perspective of the problem.

Demonstration Video

https://www.youtube.com/watch?v=Nsazb0cxeR8



References

- [Medium Article on `NMAP` Detection using Wireshark]
- [Unix Stack Exchange - Detecting `NMAP` Scans]

External Dependencies

- `pyshark`