# Deep Learning for Malicious Flow Detection

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## Goal

To identify potential malware network traffic and classify Ransomware family via machine learning.

- Malware traffic identification
- Ransomware family classification

## Feature Extraction

- Connection Records : port, IP, and protocol information in traffic flows from the transport layer.
- Network Packet Payload : extract all the payloads from each packet where the length of each packet ranges from 0 to 1,500 bytes.
- Flow Behavior : inter-arrival time of each packet and Markov transition matrix to represent the flow behavior and document the before-and-after relationship.

## Quantity Dependent Backpropagation (QDBP)

To mitigate imbalance data issue, we introduce a vector F into backpropagation and propose a QDBP algorithm which takes the disparity between classes into consideration and shows different sensitivities toward different classes. The mathematical formula is given by:

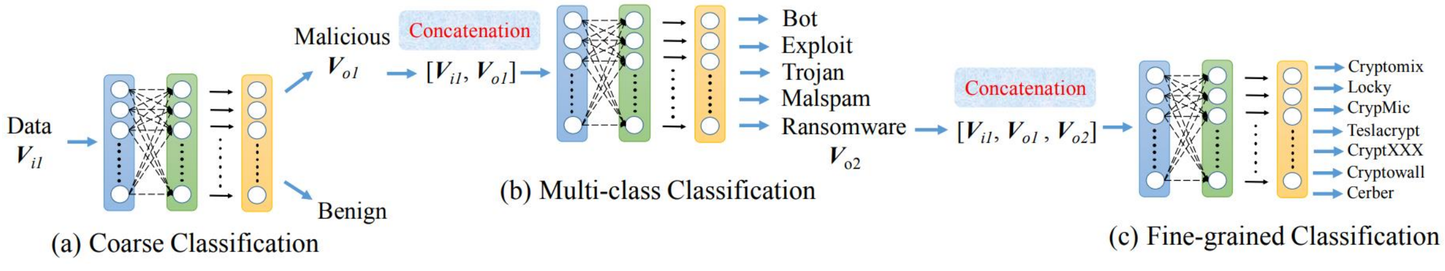
$$\theta_i^{l^+} = \theta_i^l - \eta \cdot \mathrm{F} \cdot \nabla Loss$$

$$\mathrm{F} = \left[\frac{c_1}{n_1}, \frac{c_2}{n_2}, \ldots, \frac{c_N}{n_N}\right]$$

$$\nabla Loss = \left[\frac{\partial Loss_1}{\partial \theta_i}, \frac{\partial Loss_2}{\partial \theta_i}, \ldots, \frac{\partial Loss_N}{\partial \theta_i}\right]^T$$

## Tree-Shaped Deep Neural Network (TSDNN)

To mitigate the imbalanced data issue, we propose an end-to-end trainable TSDNN model which classifies the data layer by layer. We define each model in TSDNN as a nodal network and the links between nodal networks are called bridges. We adopt cross entropy as the loss function and apply QDBP to each nodal network to optimize the performance.

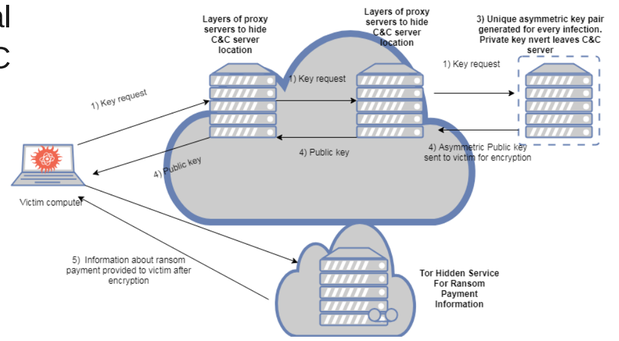



## Dataset Overview

| Class | Number of Flows | Size |
|---|---|---|
| Benign | 246,015 | 560.2 MB |
| Bot | 99 | 6.5 MB |
| Exploit | 349 | 32.5 MB |
| Trojan | 3,085 | 18.1 MB |
| Malspam | 3,612 | 142.1 MB |
| Cryptomix | 90 | 2.0 MB |
| Locky | 229 | 9.3 MB |
| CrypMic | 390 | 14.3 MB |
| Telslacrypt | 755 | 26.5 MB |
| CryptXXX | 1,259 | 44.7 MB |
| Cryptowall | 2,864 | 34.7 MB |
| Cerber | 23,260 | 23.5 MB |
| Total | 282,007 | 914.4 MB |

## Ransomware Overview

- Victim makes initial key request to C&C server
- C&C server returns encryption Public key
- Tor Hidden Service For Ransom Payment Information




## Malware traffic identification Results

| Method | Accuracy | Precision |
|---|---|---|
| DNN + Backpropagation | 59.08% | 8.33% |
| DNN + Oversampling (10000 samples/class) | 85.18% | 65.9% |
| DNN + Undersampling (45 samples/class) | 68.89% | 49.45% |
| DNN + Incremental Learning | 78.84% | 71.23% |
| DNN + QDBP | 84.56% | 62.3% |
| SVM (RBF) | 83.87% | 38.8% |
| Random Forest | 98.9% | 68.25% |
| **TSDNN + QDBP** | 99.63% | 85.4% |

Key Flow Features

- Packet inter-arrival times
- Network Packet Payload
- Markov transition matrix

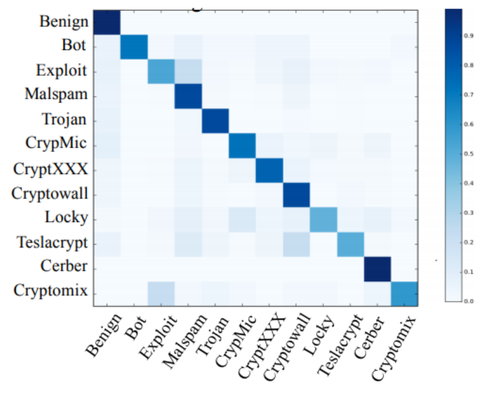
## Ransomware family classification

Goal

- Minimize false positives

Performance

- Precision: 0.964
- Recall: 0.943
- F1 Score: 0.952
- AUC of ROC: 0.971




Key Flow Features

- Packet inter-arrival times
- Network Packet Payload
- Http Request

## Discussion

The experimental results show that our model is able to accurately detect the potential malware which also justifies that behavior-oriented approach is better than signature-oriented methods when detecting malware.