Attack vs Benign Network Intrusion Traffic Classification

M. Andrecut
May 6, 2022

Calgary, Alberta, Canada
mircea.andrecut@gmail.com

Abstract
Intrusion detection systems (IDS) are used to monitor networks or systems for attack activity or policy violations. Such a system should be able to successfully identify anomalous deviations from normal traffic behavior. Here we discuss the machine learning approach to building an anomaly-based IDS using the CSE-CIC-IDS2018 dataset. Since the publication of this dataset a relatively large number of papers have been published, most of them presenting IDS architectures and results based on complex machine learning methods, like deep neural networks, gradient boosting classifiers, or hidden Markov models. Here we show that similar results can be obtained using a very simple nearest neighbor classification approach, avoiding the inherent complications of training such complex models. The advantages of the nearest neighbor algorithm are: (1) it is very simple to implement; (2) it is extremely robust; (3) it has no parameters, and therefore it cannot overfit the data. This result also shows that currently there is a trend of developing over-engineered solutions in the machine learning community. Such solutions are based on complex methods, like deep learning neural networks, without even considering baseline solutions corresponding to simple, but efficient methods.

Keywords: intrusion detection systems, machine learning, deep learning, nearest neighbor.

1 Introduction
Anomaly detection in network traffic is an important aspect of information security, and a frequently used method for detecting zero day attacks. Intrusion detection systems (IDS) are required to monitor networks or systems in order to detect anomalous patterns caused by network attacks, using machine learning algorithms [1]-[21].

IDS are typically classified into two categories, according to their detection type: (1) signature-based; and (2) anomaly-based methods. A signature-based IDS is similar to anti-virus software that can detect malicious patterns known as signatures. This type of IDS has high accuracy and low false-positive rate for known attacks, but they have no mechanism to detect novel attacks. The anomaly-based IDS uses machine learning techniques to detect anomalous traffic. This type of IDS usually has a higher false-positive rate, and the inconvenience of training a model, which in turn requires a good training data set [1].
Here we discuss the machine learning approach to building an anomaly-based IDS using the CSE-CIC-IDS2018 dataset \[21\]. Since its publication, the CSE-CIC-IDS2018 dataset has been frequently used to train IDS based on machine learning methods, and it has been adopted as a benchmark for anomaly-based IDS implementations \[11\]-\[20\]. Interestingly, most of these implementations are based on complex solutions like deep learning neural networks, random forest and gradient boosting classifiers, or hidden Markov models. While all these implementations report very good results, deep learning methods stand out by reporting a stellar 0.99 accuracy. However, all these papers fall short in comparing their results to other methods. In contrast to the above papers, here we show that similar results can be obtained using a very simple nearest neighbor classification approach, avoiding the inherent complications of training deep learning neural networks or other complex classifiers. The advantages of the nearest neighbor algorithm are: (1) it is very simple to implement; (2) it is extremely robust; (3) it has no parameters, and therefore it cannot overfit the data.

Our investigation also shows that currently there is a trend of developing over-engineered solutions in the machine learning community. Such solutions are based on complex methods, like deep learning neural networks, without even considering baseline solutions corresponding to simple, but efficient methods.

2 The CSE-CIC-IDS2018 dataset

The CSE-CIC-IDS2018 dataset was published by the Communications Security Establishment (CSE) and the Canadian Institute for Cybersecurity (CIC) \[21\]. The CSE-CIC-IDS2018 dataset includes benign samples and samples corresponding to several different attack scenarios, including: Brute-force, Denial of Service (DoS), Web attacks, Botnet, and Infiltration.

The data is organized in seven CSV files, where each row is a sample, labeled as benign or with the name of the corresponding attack, and it consists on 80 traffic features extracted using CICFlowMeter \[22\]. After downloading the data, we cleaned the data using the Python script provided by \[23\]. That is, we dropped the samples with missing feature values, and removed the columns with no values. In addition, we also dropped the timestamp, since it doesn't play any role in the classification. Table 1 shows the statistics summary of the data after the cleaning process.

3 Data normalization

Our intention is to use the 5-fold validation approach. So, for each file we split the data in 5 equal parts, we use 4 parts (80%) for "training" and 1 part (20%) for "testing". That is, for each data file we use 5 "training-testing" iterations, and we take the average of the metrics (precision, recall, accuracy, and the F-measure). Let us assume that \( D = \{d_j | j = 1, ..., J\} \) is the data corresponding to a data file, \( Y = \{y_n | n = 1, ..., N\} \) is the "training" set and \( X = \{x_m | m = 1, ..., M\} \) is the "testing" set in such an iteration. We also assume that \( C_D = \{c_j | j = 1, ..., J\} \) are the binary labels corresponding to \{benign, attack\} \( \equiv \{0, 1\} \). Consequently we have \( C_Y = \{c_n^Y | n = 1, \ldots, N\} \) and

\[{}^1\text{There may be also other papers we are not aware of, we apologise for not mentioning them here.}\]
Table 1: Summary of the CSE-CIC-IDS2018 dataset.

| Data File     | Traffic Type         | Number of Samples |
|---------------|----------------------|-------------------|
| 02-14-2018.csv| Benign               | 663,808           |
|               | FTP-BruteForce       | 193,354           |
|               | SSH-Bruteforce       | 187,589           |
| 02-15-2018.csv| Benign               | 988,050           |
|               | DoS-GoldenEye        | 41,508            |
|               | DoS-Slowloris        | 1,099             |
| 02-16-2018.csv| Benign               | 446,772           |
|               | DoS-SlowHTTPTest     | 139,890           |
|               | DoS-Hulk             | 461,912           |
| 02-22-2018.csv| Benign               | 1,042,603         |
|               | BruteForce-Web       | 249               |
|               | BruteForce-XSS       | 79                |
| 02-23-2018.csv| Benign               | 1,042,301         |
|               | BruteForce-Web       | 362               |
|               | BruteForce-XSS       | 151               |
|               | SQL-Injection        | 53                |
| 03-01-2018.csv| Benign               | 235,778           |
|               | Infiltration         | 92,403            |
| 03-02-2018.csv| Benign               | 758,334           |
|               | BotAttack            | 286,191           |
| Binary Class  | Benign               | 5,177,646         |
|               | Attack               | 1,414,765         |

\[ C_X = \{c_m^X|m = 1, ..., M\} \] the binary labels of the "training", and respectively "testing" data sets. Obviously for each of the 5-fold iterations we have: \( J = N + M, N/J \simeq 0.8, M/J \simeq 0.2, \) and \( D = X \cup Y, C_D = C_X \cup C_Y. \)

As mentioned above, each data row is represented as a vector with \( K \) columns, corresponding to the features extracted by the CICFlowMeter:

\[
d_{jk} = [d_{j1}, ..., d_{jK}], j = 1, ..., J. \tag{1}
\]

In order to use the "dot product similarity" as a metric for the nearest neighbor algorithm we have to normalize the data such that each \( d_j \) vector becomes a unit vector in the \( K \)-dimensional feature space. The normalization consists of two steps. In the first step we standardize each column using the Z-score approach. That is for each column \( k \) we calculate the mean \( \mu_k \) and standard deviation \( \sigma_k \) an we normalize the column as following:

\[
d_{jk} \leftarrow (d_{jk} - \mu_k)/\sigma_k, \quad j = 1, ..., J, k = 1, ..., K. \tag{2}
\]

The second step consists in normalizing the row vectors using the Euclidean norm:

\[
d_j \leftarrow d_j/\|d_j\|, \quad j = 1, ..., J. \tag{3}
\]
4 The Nearest Neighbor algorithm

After the normalization, all the data rows have the property \( \|d_j\| = 1 \), and therefore the "similarity" \( s(d_i, d_j) \) between two vectors \( d_i \) and \( d_j \) can be easily measured using the dot product:

\[
s(d_i, d_j) = \langle d_i, d_j \rangle = \|d_i\|\|d_j\| \cos(d_i, d_j) = \cos(d_i, d_j) \in [-1, 1].
\] (4)

Thus, two vectors are "similar" if they are colinear, such that the cosine of their angle is \( \cos(d_i, d_j) = 1 \), also they are dissimilar if they are orthogonal, that is \( \cos(d_i, d_j) = 0 \). Obviously, for \( \cos(d_i, d_j) = -1 \) the vectors are pointing in opposing directions.

In order to "classify" a "test" sample \( x_m \) we simply calculate the matrix-vector product:

\[ p_m = Y x_m = [p_{m1}, ..., p_{mN}] . \] (5)

The result \( p_m \) is a vector of length \( N \) corresponding to the projection of \( x_m \) onto all the vectors from matrix \( Y \) with the rows corresponding to the "training" data set. Then we select the index of the element with the maximum value in the vector \( p_m \):

\[ n = \arg \max_n [p_{m1}, ..., p_{mN}] . \] (6)

After the index \( n \) is determined, the classification of \( x_m \) consists in assigning it the label \( c_n^Y \) from the "training" data set. The result of the classification is:

- True positive (TP) if:
  \[
  c_n^Y = c_m^X = 1 ,
  \] (7)

- True negative (TN) if:
  \[
  c_n^Y = c_m^X = 0 ,
  \] (8)

- False positive (FP) if:
  \[
  c_n^Y = 1 \text{ and } c_m^X = 0 ,
  \] (9)

- False negative (FN) if:
  \[
  c_n^Y = 0 \text{ and } c_m^X = 1 .
  \] (10)

In order to characterize the performance of the nearest neighbor classifier we use the following metrics averaged over the 5-fold iterations:

- Precision:
  \[
  P = \frac{TP}{TP + FP} .
  \] (11)

- Recall:
  \[
  R = \frac{TP}{TP + FN} .
  \] (12)
• Accuracy:
\[ A = \frac{TP + TN}{TP + FP + TN + FN}. \] (13)

• F-measure:
\[ F = \frac{2PR}{P + R}. \] (14)

5 Numerical Results

The obtained results for the nearest neighbor algorithm are given in Table 2.

Table 2: Nearest neighbor algorithm results for the CSE-CIC-IDS2018 dataset.

| Data File        | Accuracy | F-measure | Precision | Recall |
|------------------|----------|-----------|-----------|--------|
| 02-14-2018.csv   | 0.9999   | 0.9999    | 0.9999    | 1.0000 |
| 02-15-2018.csv   | 0.9999   | 0.9997    | 0.9996    | 0.9998 |
| 02-16-2018.csv   | 0.9999   | 0.9999    | 0.9999    | 0.9999 |
| 02-22-2018.csv   | 0.9999   | 0.9910    | 0.9822    | 1.0000 |
| 02-23-2018.csv   | 0.9998   | 0.8765    | 0.8806    | 0.8725 |
| 03-01-2018.csv   | 0.7161   | 0.4564    | 0.4960    | 0.4227 |
| 03-02-2018.csv   | 0.9999   | 0.9999    | 0.9999    | 0.9999 |
| All data         | 0.9858   | 0.9667    | 0.9715    | 0.9621 |

One can see that with the exception of the 03-01-2018.csv file the results are quite astonishing for such a simple method. However, the results obtained with the other more complex methods, including deep learning neural networks also show a bad performance in the case of 03-01-2018.csv [1]-[20], with comparable values. This is due to the high similarity of attack and benign patterns for this particular data file. In fact, even in this extreme case the results obtained with the nearest neighbor algorithm are comparable to the results reported using deep learning [20] (Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM)), as shown in Table 3.

Table 3: Nearest neighbor algorithm and deep learning results [20] for the 03-01-2018.csv data.

| ML Method         | Accuracy | F-measure | Precision | Recall |
|-------------------|----------|-----------|-----------|--------|
| Nearest Neighbor  | 0.7161   | 0.4564    | 0.4960    | 0.4227 |
| CNN with PCA      | 0.7642   | 0.3463    | 0.7896    | 0.2218 |
| CNN with Autoencoder | 0.7609 | 0.3421    | 0.7595    | 0.2208 |
| LSTM with PCA     | 0.7891   | 0.4852    | 0.7757    | 0.3530 |
| LSTM with Autoencoder | 0.7814 | 0.4407    | 0.7878    | 0.3059 |

The CNN and LSTM results show a better accuracy and precision, however the nearest neighbor method provides a much better F-measure and recall, showing that it deals better with such an unbalanced data set. This result also shows that the deep learning methods overfit the data in this particular case.
Besides the fact that the results of the nearest neighbor method are similar to those obtained using "expensive" deep learning methods, we should mention that the nearest neighbor approach does not actually need training; it only needs data normalization. In contrast, the deep learning methods needed something like 19441.55 min (13.5 days) of training, as reported in [2].

Conclusion

Here we have investigated the machine learning approach to building an anomaly-based IDS using the CSE-CIC-IDS2018 dataset. We have shown that a simple nearest neighbor method provides similar results to the more "expensive" deep learning methods. The advantages of the nearest neighbor algorithm over the deep learning approach are: (1) it is very simple to implement; (2) it is extremely robust; (3) it has no parameters, and therefore it cannot overfit the data.

In the light of the obtained results, we conclude that in the case of the CSE-CIC-IDS2018 dataset the deep learning approach (or other complex machine learning method) does not provide any advantage over the much more simple nearest neighbor method.

This result also shows that currently there is a trend of developing over-engineered solutions in the machine learning community. Such solutions are based on complex methods, like deep learning neural networks, without even considering baseline solutions corresponding to simple, but efficient methods.

References

[1] Atefinia R, Ahmadi M. Network intrusion detection using multi-architectural modular deep neural network. J. Supercomput. 2020.

[2] Basnet RB, Shash R, Johnson C, Walgren L, Doleck T. Towards detecting and classifying network intrusion traffic using deep learning frameworks. J. Internet Serv. Inf. Secur. 2019, 9(4):1-17.

[3] Catillo M, Rak M, Villano U. 2l-zed-ids: A two-level anomaly detector for multiple attack classes. In: Workshops of the International Conference on Advanced Information Networking and Applications. 2020. p. 687-696.

[4] Chadza T, Kyriakopoulos KG, Lambotharan S. Contemporary sequential network attacks prediction using hidden Markov model. In: 2019 17th International Conference on Privacy, Security and Trust (PST), 2019. p. 1-3.

[5] D’hooge L, Wauters T, Volckaert B, De Turck F. Inter-dataset generalization strength of supervised machine learning methods for intrusion detection. J. Inf. Secur. Appl. 2020;54:102564.

[6] Ferrag MA, Maglaras L, Moschouiannis S, Janicke H. Deep learning for cyber security intrusion detection: approaches, datasets, and comparative study. J. Inf. Secur. Appl. 2020;50:102419.
[7] Lima Filho FSd, Silveira FA, de Medeiros Brito Junior A, Vargas-Solar G, Silveira LF. Smart detection: an online approach for dos/ddos attack detection using machine learning. Security and Communication Networks 2019.

[8] Fitni QRS, Ramli K. Implementation of ensemble learning and feature selection for performance improvements in anomaly-based intrusion detection systems. In: 2020 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT), 2020. p. 118-124.

[9] Gamage S, Samarabandu J. Deep learning methods in network intrusion detection: a survey and an objective comparison. J. Netw. Comput. Appl. 2020;169:102767.

[10] Hua Y. An efficient traffic classification scheme using embedded feature selection and lightgbm. In: 2020 Information Communication Technologies Conference (ICTC), 2020. p. 125-130.

[11] Huancayo Ramos KS, Sotelo Monge MA, Maestre Vidal J. Benchmark-based reference model for evaluating botnet detection tools driven by traffic-flow analytics. Sensors. 2020;20(16):4501.

[12] Kanimozhi V, Jacob TP. Artificial intelligence based network intrusion detection with hyperparameter optimization tuning on the realistic cyber dataset cse-cic-ids2018 using cloud computing. In: 2019 International Conference on Communication and Signal Processing (ICCSP), 2019, p. 0033-0036.

[13] Kanimozhi V, Jacob TP. Calibration of various optimized machine learning classifiers in network intrusion detection system on the realistic cyber dataset cse-cic-ids2018 using cloud computing. Int. J. Eng. Appl. Sci. Technol.2019;4(6):2143-455.

[14] Karatas G, Demir O, Sahingoz OK. Increasing the performance of machine learning-based idss on an imbalanced and up-to-date dataset. IEEE Access. 2020;8:32150-62.

[15] Kim J, Kim J, Kim H, Shim M, Choi E. Cnn-based network intrusion detection against denial-of-service attacks. Electronics. 2020;9(6):916.

[16] Li X, Chen W, Zhang Q, Wu L. Building auto-encoder intrusion detection system based on random forest feature selection. Comput. Secur. 2020;95:101851.

[17] Lin P, Ye K, Xu C-Z. Dynamic network anomaly detection system by using deep learning techniques. In: International Conference on Cloud Computing. Springer; 2019, 161-176.

[18] Zhao F, Zhang H, Peng J, Zhuang X, Na S-G. A semi-self-taught network intrusion detection system. Neural. Comput. Appl. 2020;32:17169-79.

[19] Leevy JL, Khoshgoftaar TM. A survey and analysis of intrusion detection models based on CSE-CIC-IDS2018 Big Data. J. Big Data, (2020) 7:104, 2-19.

[20] Antunes M, Oliveira L, Seguro A, VerÃssimo J, Salgado R, Murteira T. Benchmarking Deep Learning Methods for Behaviour-Based Network Intrusion Detection. Informatics, 2022, 9, 29, 1-18.
[21] I. Sharafaldin, A. H. Lashkari, A. A. Ghorbani, *Toward Generating a New Intrusion Detection Dataset and Intrusion Traffic Characterization*, 4th International Conference on Information Systems Security and Privacy (ICISSP), Portugal, January 2018.

[22] https://github.com/CanadianInstituteForCybersecurity/CICFlowMeter

[23] https://github.com/rambasnet/DeepLearning-IDS