A Model for Generating Synthetic Network Flows and Accuracy Index for Evaluation of Anomaly Network Intrusion Detection Systems

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Abstract

Objectives: This study proposes a model for generating synthetic network flows inserting malicious fragments randomly and a new metric for measuring the performance of an Anomaly Network Intrusion Detection System (ANIDS). Method: A simulation model is developed for generating synthetic network flows inserting malicious fragments that reflect Denial of Service (DoS) and Probe attacks. An ANIDS shall maximize true positives and true negatives which is equivalent to minimizing Type-I and Type-II errors. The geometric mean of True Positive Rate (TPR) and True Negative Rate (TNR) is proposed as a metric, namely, Geometric Mean Accuracy Index (GMAI) for measuring the performance of any proposed ANIDS. Findings: The task of detecting anomalous network flows by inspecting at fragment level boils down to discrete binary classification problem. The Receiver Operating Characteristic (ROC) curve considers False Positive Rates (FPR) and True Positive Rate (TPR) only. It does not reflect the minimization of Type-I and Type-II errors. Maximizing GMAI is the reflection of minimizing 1-GMAI which is equivalent to minimizing Type-I and Type-II errors. Further, the GMAI can be employed as service level for evaluating acceptance sampling based ANIDS. The domain of DoS and Probe attacks, mostly employed by the intruders at fragment level is studied. A conceptual simulation model is developed for generating synthetic network flows incorporating malicious fragments randomly from the domain of DoS and Probe attacks. The conceptual model is translated into operational model (a set computer programs) and synthetic network flows are generated. Using the operational model, the 1000 synthetic network flows are generated for each percentage of anomalous flows varying from 0.1 to 0.9 and employing discrete uniform probability distribution for selecting a fragment for transforming it into malicious. The generated network flows for each percentage of anomalous flows are represented graphically as histogram. It is found that they follow discrete uniform distribution. Hence, the model is validated. Applications: The simulation model can be used for generating synthetic networks flows for evaluating ANIDS. The GMAI can be used as service level for evaluating a discrete binary classifier irrespective of domain.

Keywords: Anomalous Flows, Geometric Mean Accuracy Index, Network Intrusion Detection Systems, Synthetic Network Flows, Simulation Model

1. Introduction

Significant, sensitive and proprietary data of a business organization, in storage and transit, are vulnerable for intrusion as internet is used widely nowadays. An intruder undertakes a set of actions that forces to compromis...
Receiver Operating Characteristic (ROC) Curve is employed for performance evaluation of an ANIDS. This study proposes a new index referred to as Geometric Mean Accuracy Index (GMAI) which proves to be more appropriate than ROC curve. Further, the Expected Opportunity Cost (EOC) of a classifier is also formulated and suggested that GMAI can be used as surrogate to service level to select the ANIDS.

The availability of real-life and benchmark data sets for network flows for performance evaluation of ANIDSs is limited. Further, the applicability of such data sets suffers from insufficiency of attack information. Hence, there is a need for synthetic data sets for network flows at fragment level. This study proposes a model for generating such data sets.

The rest of the paper is organized as follows: Section 2 reviews related work. Section 3 reviews Real-life and Benchmarks datasets. Section 4 proposes a model for generating synthetic network flows; Section 5 proposes a new performance metric, GMAI and an Opportunity Cost model for evaluating ANIDS. Section 6 presents conclusion of the study.

2. Review of Network Security Issues

The Transmission Control Protocol/Internet Protocol (TCP/IP) suite provides data transmission services for applications on internet. An intruder strives to gain unauthorized access to a system violating network security with the intension of interfering with system Confidentiality, data Integrity and Availability (CIA). The state of keeping information, in storage or transit, understandable to intended receivers only is referred to as confidentiality of information. Availability of information refers ensuring legitimate users to access information when needed. The ability of detecting any alteration of information, in storage or transit, is referred to as integrity. The act of ensuring a creator/sender of the information to comply with the same at later time is referred to as non-repudiation. The conformity of identities of sender and receiver with each other and the origin/destination of the information is referred to as authentication.

Cryptography is the science and art of protecting information by encrypting it into cipher text. Only with a secret key can decrypt the message into plain text. The primary objectives of cryptography are to: maintain confidentiality, ensure availability, preserve integrity, enforce non-repudiation and grant authentication.

Cryptography cannot monitor and analyze network traffic data, user activities such as failed login attempts guessing password with invalid/valid User ID, attempts to use privileges that have not been authorized and system activities such as system resources utilization, hardware policy violations etc. Further, it cannot protect against transfer of virus.

The use of firewalls to monitor the network traffic data for allowing it subjected to specific rules. However, a firewall fails to provide protection against malicious insiders, new threats and transfer of virus. An Intrusion Detection System (IDS) that is able to identify attacks against vulnerable services and applications, privilege violations, unauthorized logins and access to sensitive files. An IDS is a dynamic monitoring system whereas a firewall is a static monitoring system.

An IDS is primarily classified into Host-based Intrusion Detection System (HIDS) and Network-based Intrusion Detection System (NIDS). An HIDS, deployed at host level, collects data from log files and verifies login, logoff, and modification of data. It also verifies access information to system resource like files/memorystorage/registry. NIDS, deployed at network level, verifies network traffic data by observing packet information. It also collects information from network Management Information Base (MIB).

Based on the detection mechanism, the NIDSs are classified into three types as given hereunder:

1. Misuse-Based NIDS (MNIDS)
   It is also known as signature-based NIDS that employ a set of rules for detecting known attacks.

2. Anomaly-Based NIDS (ANIDS)
   It attempts to detect unknown attacks, abnormal patterns in network traffic data not matching with expected normal patterns.

3. Hybrid NIDS (HNIDS)
   It exploits the merits of the above two approaches for detecting both known and unknown attacks.

As this study considers ANIDS only, its brief description is presented here referring the generic view of its architecture shown in Figure 1. An anomaly detection engine comprises pre-processing and matching mechanism as software components. It receives a packet from internet as input through pre-processing module and outputs an alarm on detecting anomalous pattern of the packet. The pre-processing module captures a packet and
organizes its data suitable for matching mechanism as input. The classification algorithm of matching mechanism detects the anomalous behavior of a packet making use of the configuration and reference data. The alarm forms the basis for intrusion mitigation, monitoring, and management; and updating configuration and reference data. The information about known intrusion signatures or profiles of normal behavior is stored as reference data whereas the intermediate results are stored as configuration data. The analysis and interpretation of alarm information for diagnosing actual attacks is referred to as post-processing. The post-processing is carried by human analyst and post-processing module. Whenever new intrusions are known as a result of post-processing, the security manager updates intrusion signatures.

Figure 1. ANIDS architecture.

The network attacks detected by ANIDS are classified as:

1. **Remote to Local Attack (R2L)**
The intruders send packets to system over a network and make use of vulnerability to gain local access.

2. **Probing Attack (PROBE)**
The intruder attempt to gather information about systems i.e., how many and what types of systems are on the network and what services the system supports for the purpose of intrusion.

3. **Users to Root Attack (U2R)**
The intruder access to a normal user accounts on the system exploits weak or mis-configured system security policies, operating systems log files to gain access to root.

4. **Denial of Service Attack (DoS)**
These attacks prevent legitimate users accessing a host or using network resources / services. Grouped the attacks as shown in the following Table 1.

| Attack Categories | DoS                        | Probe                      | U2R                      | R2L                      |
|-------------------|----------------------------|----------------------------|--------------------------|--------------------------|
|                   | Land, Teardrop             | Host scan, msnad           | Perl, exit              | dictionary               |
|                   | Fraggle, Xmas.             | nmap, saint                | xterm, eject            | ftp-write                |
|                   | Rose, Winnuwe, nestea      |                            | fdformat                | guest                    |
|                   | Neptune, Ping Of Death,    |                            | ps, loadmodule          | phf                      |
|                   | Smurf, Apache2, Back       |                            |                          | xlock                    |

The DoS attacks consume prohibitively high level of resources such as link bandwidth, CPU processing power and memory storage leading to disruption of services. In 2013, it was found that 60 percent of companies were affected by DoS attacks more than once with the probability of 0.87. By 2015, 73 percent of companies are affected by DoS attacks. The tools for detecting and mitigating DoS attacks at host and network level are provided. The demand for such tools has grown up to 70% by 2015 out of which the demand for network level specific tools is around 78%.

The description and impact of DoS and PROBE attacks is presented in the Table 2. Here, the Pareto principle is applicable as 95% of network traffic is handled by TCP/UDP protocols and the demand for network level specific tools for mitigating DoS attacks is 78%. Hence, it is felt appropriate to develop a model for generating synthetic network flows inserting DoS and PROBE attacks at fragment level. Such synthetic data are immensely useful for evaluating the effectiveness of ANIDS as the real-life data are scarce.

### 3. Review on Datasets

For evaluating the effectiveness and efficiency of ANIDS, appropriate datasets are required. It is preferable to employ benchmark or real-life datasets.

The data generated from simulated environments of several networks for different attack scenarios is referred to as benchmark data. The data collected over a period of time from real-life network traffic prone to attacks constitute real-life datasets.

The benchmark datasets are provided in DEFCON, CAIDA, LBNL, and KDDcup99 and NSL-KDD. The DEFCON datasets reflects in limited way real-life network traffic. The CAIDA and LBNL datasets are heavily anonymized. The KDDcup99 and NSL-KDD datasets are not fragment-based datasets.
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The Kyoto, MAWI, ISCX-UNB, and UNIBS are realistic datasets available for researchers. The Kyoto dataset is prepared from network traffic traces collected from a honey pot connected to an internet. By design, the honey pot captures unusual traffic and it does not reflect real-life scenarios. For the context, fragment-based datasets are applicable whereas MAWI is a flow-based dataset. The ISCX-UNB and UNIBS are raw traffic traces but do not contain attack data. It is obvious that the intruders insert DoS and PROBE attacks as listed in Table 2 by changing one or more fragments of a network flow. The above datasets lack of requisite data for evaluating ANIDS in the context of DoS and PROBE attacks. Hence, it is motivated to develop a model for generating synthetic network flow datasets at fragment level that reflects real-life traffic.

4. A Model for Generating Synthetic Network Flows

This study proposes a model to generate synthetic network flows inserting DoS and PROBE attacks at fragment level that would be useful for evaluating the effectiveness of any proposed ANIDS by researchers.

A network flow is partitioned into a Number of Packets (NoP) and in turn each packet is divided into a number of fragments. Ultimately, a network flow is a set of fragments passing through an observation point in a network. The attributes of each fragment of a network flow are as follows: Flow Number, Packet Identity, Fragment Identity, Source IP, Destination IP, Source Port, Destination Port, Protocol, Urgent Flag, Acknowledgement Flag, Push Flag, Reset Flag, Synchronous Flag, Final Flag, More Fragment Flag, Length of Fragment and Fragment Offset.

Table 2. Description and impact of DoS and PROBE attacks

| S.No | Attack | Protocol | Attack Category | Attack Description | Impact |
|------|--------|----------|----------------|--------------------|--------|
| 1    | LAND   | TCP      | DoS            | Source IP is spoofed as destination IP and it sends ACK to itself. | Destination is frozen |
| 2    | Xmass  | TCP      | DoS            | URG, PSH and FIN flags are set | Destination is rebooted |
| 3    | Nestea | TCP      | DoS            | Fragment offset is changed | Operating system is crashed |
| 4    | Rose   | TCP      | DoS            | Intentionally too small fragment is crafted which would be identified during packet reassembling at destination | Processor resources are exhausted |
| 5    | Win nuke | TCP  | DoS            | Sends fragment to destination port 139 over NetBIOS setting URG flag | Operating system is crashed |
| 6    | Tear drop | UDP | DoS            | Fragment offset is changed | Operating system is crashed |
| 7    | Fraggle | UDP      | DoS            | Connection request is broadcasted spoofing victim's IP address as source IP so that all hosts which receive the request respond | Network and processor resources are exhausted |
| 8    | Port Scan | TCP/UDP | PROBE           | Spoofed source IP sends fragments varying destination ports | Vulnerable ports are found |
| 9    | Host Scan | TCP/UDP | PROBE           | Spoofed source IP sends fragments to different destination hosts | Vulnerable host are found |

An intruder gets access to the fragments of network flow, in transition from a source to a destination, and inserts the malicious data in one or more fragments.
transforming the flow as anomalous flow. The formats of normal and anomalous fragments affected with DoS / PROBE attacks of a network flow are presented Tables 3 and Table 4. A model is developed for generating synthetic anomalous flows. Its input parameters and data assumptions are given in Table 5 and Table 6. The overall processing logic of the model for generating synthetic network flows is given in Figure 2. Line 1 is to read the input viz., Maximum Number of Flows (MNF), S, D, CSP, CDP and P. The lines 2-5 initialize MFS, MPS, MTU and Flow Number (FN). The loop (while) between the lines 6 and 24 is for generating the normal / malicious fragments for each network flow. The lines 7 to 13 generate random variates that represent seven attributes of a network flow.

The function TCP-NORMAL-FLOW (F) generates TCP normal flows. Lines 1-2 computes NoP of maximum size and Residual Packet (RP) for the network flow size. The For loop in lines 3-9 generate fragment level network flow records for all packets of a flow and lines 10-16 generate fragment level records for RP. These network flow records are appended to the TCP Normal Flow file tn in Figure 3.

The For loop in lines 4-20 of the function TCP-ANOMALOUS-FLOW (F) generate fragment level anomalous network flow record if FrT is malicious else generate Normal network flow record and lines 21-38 generate for residual packet as shown in Figure 4.

The function TCP-ATTACK (T, F) calls corresponding attack function based on T. Each attack function inflicts the attack. The attributes of fragment level flow records for attacks are given in Table 5 and normal flow is given in the Table 6. The anomalous flow records are appended to the TCP anomalous Flow file ta in Figure 4. The pseudo code for TCP attacks is given in Figures 4(a) to 4(i).

### Table 3. Normal fragments

| Attack       | SIP | DIP | SP | DP | Proto | FLAGS | length | FO          |
|--------------|-----|-----|----|----|-------|--------|--------|-------------|
| Normal       | X   | Y   | P  | Q  | TCP   | 0 1 0 0 0 0 1 | EQ MTU | Multiples of offset value |
| Normal       | X   | Y   | P  | Q  | UDP   | 0 0 0 0 0 0 1 | EQ MTU | Multiples of offset value |

### Table 4. Anomalous fragments affected with DoS / PROBE attacks

| Attack       | SIP | DIP | SP | DP | Proto | FLAGS | length | FO          |
|--------------|-----|-----|----|----|-------|--------|--------|-------------|
| Land         | Y   | Y   | P  | Q  | TCP   | 0 1 0 0 0 0 | 40 0   |             |
| Xmass        | X   | Y   | P  | Q  | TCP   | 1 0 1 0 0 0 | 40 0   |             |
| Nestea       | X   | Y   | P  | Q  | TCP   | 0 1 0 0 0 0 | 40 0   |             |
| Rose         | X   | Y   | P  | Q  | TCP   | 0 1 0 0 0 0 | 40 0   |             |
| Winnuke      | X   | Y   | P  | Q  | TCP   | 1 0 0 0 0 0 | 40 0   |             |
| Port Scan    | X   | Y   | P  | Not Q | TCP  | 0 1 0 0 1 0 | 40 0   |             |
| Host Scan    | X   | Not Y | P  | Q  | TCP   | 0 1 0 0 1 0 | 40 0   |             |
| Tear drop    | X   | Y   | P  | Q  | UDP   | 0 0 0 0 0 0 | 40 0   |             |
| Fraggle      | X   | Broadcast Address | P  | Q  | UDP   | 0 0 0 0 0 0 | 40 0   |             |
| Port Scan    | X   | Y   | P  | Not Q | UDP  | 0 0 0 0 0 0 | 40 0   |             |
| Host Scan    | X   | Not Y | P  | Q  | UDP   | 0 0 0 0 0 0 | 40 0   |             |
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SYNTHETIC-FLOWS ()
1. Read MNF, S, D, CSP, CDP, P
2. MFS ← 500
3. MPS ← 65536
4. MTU ← 1500
5. FN ← 1
6. while (FN <= MNF)
7. SIP ← DURV (1, S)
8. DIP ← DURV (1, D)
9. SP ← DURV (1, CSP)
10. DP ← DURV (1, CDP)
11. Proto ← DURV (1, 2)
12. FS ← DURV (1, MFS) * 1024
13. FT ← DER (P)
14. F = (<FN, SIP, DIP, SP, DP, Proto, FS, FT>)  // Generated network flow
15. if (Proto = 1) && (FT = 1)
16. sf ← TCP-NORMAL-FLOW(F)
17. if (Proto = 1) && (FT = 0)
18. sf ← TCP-ANOMALOUS-FLOW(F)
19. if (Proto = 2) && (FT = 1)
20. sf ← UDP-NORMAL-FLOW(F)
21. if (Proto = 2) && (FT = 0)
22. sf ← UDP-ANOMALOUS-FLOW(F)
23. Write sf
24. FN ← FN + 1

Figure 2. Generation of synthetic network flows.

TCP-NORMAL-FLOW (F)

NoP = \[
\frac{FS}{MPS}
\]  // NoP of maximum packet size

RP = FS - (MPS * NoP)  // RP in bytes

for i = 1 to NoP

NoF = \[
\frac{MTU - 20}{MPS}
\]  // Number of fragments of size MTU

RF = (MPS - (MTU - 20) * NoF)  // Residual fragment in bytes

for j = 1 to NoF

tn = <FN, i, j, SIP, DIP, SP, DP, Proto, 0, 1, 0, 0, 0, 1, 1500, (j-1)*185>

if (RF = 0)

tn = <FN, i, j, SIP, DIP, SP, DP, Proto, 0, 1, 0, 0, 0, 0, (RF-20), (j-2)*185+RF/8>

if (RF = 0)

NoRF = \[
\frac{RP}{MTU - 20}
\]  // Number of fragments of RP

RPRF = (RP - (MTU - 20) * NoRF)  // Residual fragment of RP in bytes

for k = 1 to NoRF

tn = <FN, i, k, SIP, DIP, SP, DP, Proto, 0, 1, 0, 0, 0, 0, 1, 1500, (k-1)*185>

if (RPRF = 0)

tn = <FN, i, k, SIP, DIP, SP, DP, Proto, 0, 1, 0, 0, 0, 0, (RPRF-20), (k-2)*185 +(RPRF/8)>

return tn

Figure 3. Generation of TCP normal flows.
Table 6. Data assumptions

| Data Notation | Data Description | Assumption |
|---------------|------------------|------------|
| FS            | Network Flow Size| A random variate from discrete uniform distribution [1,MFS] |
| SIP           | Source IP Address| A random variate from discrete uniform [1,S] |
| SP            | Source Port      | A random variate from discrete uniform [1,CSP] |
| DP            | Destination Port | A random variate from discrete uniform [1,CDP] |
| DIP           | Destination IP Address | A random variate from discrete uniform [1,D] |
| Proto         | Protocol         | A random variate from discrete uniform [1,2] 1 indicates TCP and 2 indicates UDP |
| FT            | Flow type        | A random variate from discrete empirical [0,1] 0 indicates anomalous flow and 1 indicates Normal flow |
| FrT           | Fragment type    | A random variate from discrete empirical [0,1] 0 indicates malicious fragment and 1 indicates Normal fragment |

The function UDP-NORMAL-FLOW (F) generates UDP normal flows. Lines 1-2 computes NoP of maximum size and RP for the network flow size. The For loop in lines 3-9 generate fragment level network flow records for all packets of a flow and lines 10-16 generate fragment level network flow records for RP. These network flow records are appended to the UDP Normal Flow file un in Figure 5.

The function UDP-ANOMALOUS-FLOW (F) generates anomalous network flows. The For loop in lines 4-20 generate fragment level anomalous network flow record if FrT is malicious else generate Normal flow record and lines 21-38 generate for RP.

The function UDP-ATTACK (T, F) calls corresponding attack function based on T. Each attack function inflicts the attack. The attributes of fragment level flow records for attacks are given in Table 5 and normal flow is given in the Table: 6. The anomalous flow records are appended to the UDP anomalous Flow file ua as shown in Figure 6. The pseudocode for UDP attacks is given in Figures 6 (a) to 6 (f). The sample output is given in the Table 7.

5. Accuracy Index for Evaluation of ANIDS

Anomaly intrusion detection methods classify a network flow into either anomalous flow or normal flow. Hence, it is a binary classification problem. The detection of oil spills in satellite radar images, fraud detection in mobile communications, diagnosis of rare diseases, and text classification in information retrieval are some of typical examples of binary classification.
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12  else
13  ta ← NORMAL(F)
14  if (RF≠0)
15       FrT ← DER(P)
16       If (FrT==1)
17       T = DURV (1, NoA)
18       ta ← TCP-ATTACK (T, F)
19  else
20       ta ← NORMAL(F)
21       if (RP≠0)
22       NoRF ← \frac{RF}{MTU - 20} \geq Number of fragments of RP
23       RPRF ← (RP - (MTU - 20) * NoRF) \geq Residual fragment of RP in bytes
24       for k=1 to NoRF
25       FrT ← DER(P)
26       If (FrT==1)
27       T = DURV (1, NoA)
28       ta ← TCP-ATTACK (T, F)
29  else
30       ta ← NORMAL(F)
31       if (RPRF≠0)
32       FrT ← DER(P)
33       If (FrT==1)
34       T = DURV (1, NoA)
35       ta ← TCP-ATTACK (T, F)
36  else
37       ta ← NORMAL(F)
38  Return ta

Figure 4. Generation of TCP anomalous flows.

TCP-ATTACK (T, F)
1  CASE T OF
2       LAND-ATTACK (F)
3       XMASS-ATTACK (F)
4       NESTEA-ATTACK (F)
5       ROSE-ATTACK (F)
6       WINNUKE-ATTACK (F)
7       PORTSCAN-ATTACK (F)
8       HOSTSCAN-ATTACK (F)
END CASE

Return \( t_a \)

**Figure 4(a).** Selection of TCP attacks.

### NORMAL(F)

1. \( t_a \leftarrow <FN,i,j,SIP,DIP,SP,DP,Proto,0,1,0,0,0,1,1500,(j-1) \times 185> \)
2. Return \( t_a \)

**Figure 4(b).** TCP fragment level normal flow.

### LAND-ATTACK (F)

1. \( SIP \leftarrow DIP \)
2. \( t_a \leftarrow <FN,i,j,SIP,DIP,SP,DP,Proto,0,1,0,0,0,0,40,0> \)
3. Return \( t_a \)

**Figure 4(c).** Land attack.

### XMASS-ATTACK (F)

1. \( t_a \leftarrow <FN,i,j,SIP,DIP,SP,DP,Proto,1,0,0,1,0,0,40,0> \)

**Figure 4(d).** X mass attack.

### NESTEA-ATTACK (F)

1. \( FO \leftarrow FO \leftarrow k \times 185 \quad / 0 < k < 1 \)
2. \( t_a \leftarrow <FN,i,j,SIP,DIP,SP,DP,Proto,0,1,0,0,0,1,1500,FO> \)
3. Return \( t_a \)

**Figure 4(e).** Nestea attack.

### ROSE-ATTACK (F)

1. \( MF \leftarrow 1 \)
2. \( t_a \leftarrow <FN,i,j,SIP,DIP,SP,DP,Proto,0,1,0,0,1,400, (j-1) \times 185> \)
3. Return \( t_a \)

**Figure 4(f).** Rose attack.

### WINNUKE-ATTACK (F)

1. \( DP \leftarrow 139 \)
2. \( t_a \leftarrow <FN,i,j,SIP,DIP,SP,DP,Proto,1,1,0,0,0,1,1500, (j-1) \times 185> \)
3. Return \( t_a \)

**Figure 4(g).** Win nuke attack.

### PORTSCAN-ATTACK (F)

1. \( DP \leftarrow DURV(1,65536) \)
2. \( t_a \leftarrow <FN,i,j,SIP,DIP,SP,DP,Proto,0,0,0,1,0,40,0> \)
3. Return \( t_a \)

**Figure 4(h).** Port scan attack.

### HOSTSCAN-ATTACK (F)

1. \( DIP \leftarrow DURV(1,50) \)
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Foster Provost et al. proposed a set of metrics based on the elements of confusion matrix. The same are described below briefly.

5.1 True Positive Rate (TPR)
TPR is the ratio between the number of true positive flows and anomalous flows refer Equation (1). It is also known as sensitivity, hit rate or recall.

\[
TPR = \frac{TP}{TP + FN}
\]  

5.2 True Negative Rate (TNR)
TNR is the ratio between the number of true negative flows and normal flows refer Equation (2). It is also known as specificity.

```
2 \( t_a \leftarrow <FN, i, j, SIP, DIP, SP, DP, Proto, 0, 0, 0, 0, 1, 0, 0, 40, 0 > \)  
3 \( \text{Return} t_a \)
```

Figure 4(i). Host scan attack.

```
| UDP-NORMAL-FLOW (F) |
|---------------------|
| \( \text{NoP} \leftarrow \frac{FS}{MPS} \) NoP of maximum packet size |
| \( \text{RP} \leftarrow FS - (MPS \times \text{NoP}) \) RP in bytes |
| \( \text{NoF} \leftarrow \frac{MPS}{MTU - 20} \) Number of fragments of size MTU |
| \( \text{RF} \leftarrow (MPS - (MTU - 20) \times \text{NoF}) \) Residual fragment in bytes |
| \( \text{for} \ j=1 \text{ to NoF} \) |
| \( \text{un} \leftarrow <FN, i, j, SIP, DIP, SP, DP, Proto, 0, 0, 0, 0, 1, 1500, (j-1) \times 185 \) |
| \( \text{if} \ (\text{RF}=0) \) |
| \( \text{un} \leftarrow <FN, i, j, SIP, DIP, SP, DP, Proto, 0, 0, 0, 0, 0, 0, (RF+20), ((j-2) \times 185+RF/8) \) |
| \( \text{if} \ (\text{RP}=0) \) |
| \( \text{NoRF} \leftarrow \frac{RF}{MTU - 20} \) Number of fragments of RP |
| \( \text{RPRF} \leftarrow (RP - (MTU - 20) \times \text{NoRF}) \) Residual fragment of RP in bytes |
| \( \text{for} \ k=1 \text{ to NoRF} \) |
| \( \text{un} \leftarrow <FN, i, k, SIP, DIP, SP, DP, Proto, 0, 0, 0, 0, 0, 0, 1500, (k-1) \times 185 > \) |
| \( \text{if} \ (\text{RPRF}=0) \) |
| \( \text{un} \leftarrow <FN, i, k, SIP, DIP, SP, DP, Proto, 0, 0, 0, 0, 0, 0, 0, (RPLF+20), (k-2) \times 185 + (RPRF/8) > \) |
| \( \text{Return un} \) |
```

Figure 5. Generation of UDP normal flows.
Table 7. Sample output of normal and anomalous network flows

| FN | i | j | SIP | DIP | SP | DP | Proto | FLAGS | length | FO | Attack |
|----|---|---|-----|-----|----|----|-------|--------|--------|----|--------|
|    |   |   |     |     |    |    |       |        |        |    |        |
| 1  | 1 | 1 | 83  | 13  | 440| 224| TCP   | U 0 A 1 P 0 R 0 S 0 F 1 | 1500  | 7585| Normal |
| 5  | 1 | 16| 44  | 44  | 906| 906| TCP   | U 0 A 1 P 0 R 0 S 0 F 1 | 40   | 0   | Land   |
| 10 | 4 | 42| 16  | 45  | 536| 424| TCP   | U 0 A 1 P 0 R 0 S 0 F 1 | 40   | 0   | Xmass  |
| 12 | 3 | 14| 71  | 4   | 237| 520| TCP   | U 0 A 0 P 0 R 0 S 0 F 1 | 1500 | 2316| Nestea |
| 21 | 2 | 1 | 42  | 16  | 536| 71 | TCP   | U 0 A 0 P 0 R 0 S 0 F 1 | 400  | 0   | Rose   |
| 49 | 3 | 4 | 81  | 44  | 965| 139| TCP   | U 0 A 0 P 0 R 0 S 0 F 1 | 1500 | 555 | Winnuke|
| 58 | 1 | 21| 78  | 50  | 730| 803| TCP   | U 0 A 1 P 0 R 0 S 0 F 1 | 40   | 0   | Port Scan|
| 61 | 1 | 29| 8   | 1   | 678| 221| TCP   | U 0 A 0 P 0 R 0 S 0 F 0 | 1500 | 3078| Teardrop|
| 4  | 1 | 6 | 83  | 13  | 440| 224| UDP   | U 0 A 0 P 0 R 0 S 0 F 1 | 1500 | 925 | Normal |
| 35 | 5 | 42| 56  | 1   | 904| 389| UDP   | U 0 A 0 P 0 R 0 S 0 F 1 | 1500 | 3078| Teardrop|
| 42 | 3 | 21| 55  | 255 | 708| 209| UDP   | U 0 A 0 P 0 R 0 S 0 F 0 | 40   | 0   | Fraggle|
| 51 | 5 | 24| 69  | 9   | 586| 67 | UDP   | U 0 A 0 P 0 R 0 S 0 F 0 | 40   | 0   | Port Scan|
| 89 | 2 | 32| 83  | 49  | 231| 1013|UDP   | U 0 A 0 P 0 R 0 S 0 F 0 | 40   | 0   | Host Scan|

UDP - ANOMALOUS - FLOW (F)

1. \( \text{NoP} \leftarrow \left\lfloor \frac{FS}{MPS} \right\rfloor \)\text{NoP of maximum packet size}
2. \( \text{RP} \leftarrow \text{FS} - (\text{MPS} \times \text{NoP}) \)\text{RP in bytes}
3. \( \text{NoA} \leftarrow 4 \)\text{Number of attacks}
4. for \( i = 1 \) to \( \text{NoP} \)
5. \( \text{NoF} \leftarrow \left\lfloor \frac{MPS}{MTU - 20} \right\rfloor \)\text{Number of fragments of size MTU}
6. \( \text{RF} \leftarrow (\text{MPS} - (\text{MTU} - 20) \times \text{NoF}) \)\text{Residual fragment in bytes}
7. for \( j = 1 \) to \( \text{NoF} \)
8. \( \text{FrT} \leftarrow \text{DER}(P) \)\text{Fragment type}
9. If (FrT==1)
10. \( \text{T} = \text{DURV}(1,\text{NoA}) \)
11. \( \text{ua} \leftarrow \text{UDP-ATTACK}(\text{T},\text{F}) \)
12. else
13. \( \text{ua} \leftarrow \text{UNORMAL}(\text{F}) \)
14. if (RF=0)
15. \( \text{FrT} \leftarrow \text{DER}(P) \)\text{Fragment type}
16. If (FrT==1)
17. \( \text{T} = \text{DURV}(1,\text{NoA}) \)
18. \( \text{ua} \leftarrow \text{UDP-ATTACK}(\text{T},\text{F}) \)
19. else
20. \( \text{ua} \leftarrow \text{UNORMAL}(\text{F}) \)
21. if (RP=0)
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```plaintext
22 \( N = \frac{R}{MTU - 20} \)

23 \( RPRF \leftarrow (R - (MTU - 20) \times N) \)

24 for \( k = 1 \) to \( N \)

25 \( FrT \leftarrow DE(P) \)

26 if \( FrT = 1 \)

27 \( T \leftarrow DURV(1, NoA) \)

28 \( ua \leftarrow UDP-ATTACK(T,F) \)

29 else

30 \( ua \leftarrow UNORMAL(F) \)

31 if \( RPRF \neq 0 \)

32 \( FrT \leftarrow DE(P) \)

33 if \( FrT = 1 \)

34 \( T \leftarrow DURV(1, NoA) \)

35 \( ua \leftarrow UDP-ATTACK(T,F) \)

36 else

37 \( ua \leftarrow UNORMAL(F) \)

38 Return ua

Figure 6. Generation of UDP anomalous flows.

UDP-ATTACK (T,F)
1 \( \text{CASE} \ T \text{ OF} \)
2 1 TEARDROP- ATTACK (F)
3 2 FRAGGLE- ATTACK (F)
4 3 UPORT SCAN- ATTACK (F)
5 4 UHOST SCAN- ATTACK (F)
6 \( \text{END CASE} \)
7 \( \text{Return} _{ua} \)

Figure 6(a). Selection of UDP attacks.

UNORMAL (F)
1 \( t_{ua} \leftarrow \text{<FN,i,j,SIP,DIP,SP,DP,Proto,0,0,0,0,1,1500,0,(j-1)*185>} \)
2 \( \text{Return} _{ua} \)

Figure 6 (b). UDP fragment level normal flow.

TEARDROP- ATTACK (F)
1 \( FOeFO \leftarrow x*185 / 0<x<1 \)
2 \( t_{ua} \leftarrow \text{<FN,i,j,SIP,DIP,SP,DP,Proto,0,0,0,0,1,1500,FO>} \)
3 \( \text{Return} _{ua} \)

Figure 6 (c). Tear drop attack.

FRAGGLE- ATTACK (F)
5.3 False Positive Rate (FPR)

FPR is the ratio between the number of false positive flows and normal flows refer Equation (3). It is also known as Type-I Error rate.

\[ FPR = \frac{FP}{FP + TN} \]  

5.4 False Negative Rate (FNR)

FNR is the ratio between the number of false negative flows and anomalous flows refer Equation (4). It is also known as Type-II Error rate.

\[ FNR = \frac{FN}{FN + TP} \]  

5.5 Positive Predictive Value (PPV)

PPV is the ratio between the number of true positive flows and the sum of true positive and false positive flows refer Equation (5). This is also called as precision.

\[ PPV = \frac{TP}{TP + FP} \]
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\[
NPV = \frac{TN}{TN + FN} \tag{6}
\]

5.7 Misclassification Rate (MCR)
MCR is the ratio between the sum of number of false negatives and false positives and total numbers of flows considered for evaluating an AINDS refer Equation (7).

\[
MCR = \frac{FP + FN}{TP + FP + FN + TN} \tag{7}
\]

5.8 Accuracy
Accuracy is the ratio between the sum of number of true positives and true negatives and total numbers of flows considered for evaluating an AINDS refer Equation (8).

\[
Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{8}
\]

The ROC curve, TPR versus FPR is used widely for evaluating the performance of classifiers\(^{24}\). A single point in ROC space is produced when a discrete classifier is applied on a test set. When a continuous classifier is applied on a test set, one point for each of the threshold values is produced in ROC space. An ROC curve is fitted through those points. The ROC curves for three different classifiers are shown in Figure 8.

The point (0, 0) represents entirely misclassification of anomalous and correct classification of normal flows. The point (1, 1) represents entirely correct classification of anomalous flows but entirely misclassification of normal flows. The point (0, 1) represents entirely correct classification of anomalous as well as normal flows. The point (1, 0) represents entirely misclassification of anomalous flows as well as normal flows. The Area under ROC Curve (AUC) is taken as a single value which ranges from 0 to 1 for presenting the performance of a classifier. Generally, it is deduced that higher the AUC better the performance of a classifier. However, it is not so as AUC 1 indicates that TPR is 1 for \(0 \leq FPR \leq 1\). It means that the anomalous flows are correctly classified irrespective of misclassification of normal flows. Hence, higher the AUC better the performance of classifier is not appropriate as it does not consider to minimize Type-I error which is also necessary.

Bo Tang et al\(^{25}\) in text categorization in information retrieval applied Geometric mean of precision (PPV) and recall (TPR) as metric to evaluate performance of classifier for multiple classes. The ANIDS is a binary classifier in which TPR and TNR is to be maximized. Hence, the geometric mean of TPR and TNR is proposed as a single measure which represents the combined accuracy of TPR and TNR. It is referred to as GMAI of a classifier. Mathematically formulation of it is given in Equation (9).

\[
MaximizeGMAI = f(TPR, TNR) = \sqrt{TPR \cdot TNR} \tag{9}
\]

It is obvious that maximizing GMAI is equivalent to minimizing \(1 - \sqrt{TPR \cdot TNR}\).

Higher the GMAI better the performance of a classifier. The relation between TPR and TNR is shown in Figure 9. Equivalently, lower the 1-GMAI better the performance of a classifier. Further, the analyst can choose GMAI based on his perception for a given situation and consider it as threshold value. A classifier whose GMAI is greater than or equal to threshold value is chosen. If it is required to choose a classifier from a set of classifiers yielding GMAIs greater than or equal to threshold value, the classifier associated with the maximum GMAI is chosen.

Figure 9. The relationship between TPR and TNR.

5.9 The Cost Model
Obviously, the sum of the elements of confusion matrix resulted as a consequence of applying a classifier on a given test data set, is the cardinality of that test data set. Then the empirical probabilities of the elements of confusion matrix are defined Equation (10) to Equation (13).

The probability of detecting anomalous flow as anomalous is defined as

\[
P_{TP} = \frac{TP}{N_0F} \tag{10}
\]

The probability of detecting anomalous flow as normal is defined as

\[
P_{FN} = \frac{FN}{N_0F} \tag{11}
\]
The probability of detecting normal flow as anomalous is defined as
\[
P_{FP} = \frac{FP}{T_{NoF}}
\]  
(12)

The probability of detecting normal flow as normal is defined as
\[
P_{TN} = \frac{TN}{T_{NoF}}
\]  
(13)

Where
\[
T_{NoF} = \text{Total Number of flows} = TP + FN + FP + TN
\]

The opportunity cost is the cost of misclassification. The EOC of a classifier is formulated as shown in Equation (14).
\[
\text{Minimize} \ EOC = C_{TP} \cdot p_{TP} + C_{FN} \cdot p_{FN} + C_{FP} \cdot p_{FP} + C_{TN} \cdot p_{TN}
\]  
(14)

Where
\[
C_{TP} = \text{Opportunity cost of classifying an anomalous flow as anomalous}
\]
\[
C_{FN} = \text{Opportunity cost of classifying an anomalous flow as normal}
\]
\[
C_{FP} = \text{Opportunity cost of classifying a normal flow as anomalous}
\]
\[
C_{TN} = \text{Opportunity cost of classifying a normal flow as normal}
\]

Obviously, the opportunity costs, \(C_{TP}\) and \(C_{TN}\) are zero as the classification done correctly. Hence, the above equation boils down to:
\[
\text{Minimize} \ EOC = C_{FN} \cdot p_{FN} + C_{FP} \cdot p_{FP}
\]

Generally, it is difficult to estimate the opportunity costs, \(C_{FN}\) and \(C_{FP}\). Whenever it is difficult to estimates the costs, service level is taken as surrogate. Here, the GMAI can be taken as surrogate for EOC for selection of a classifier or ranking of classifiers.

6. Conclusions

The real-life and benchmark datasets of network flows accessible to researchers lack the requisite data for evaluating ANIDS in the context of DoS and PROBE attacks. The present study proposes a model for generating synthetic network flows useful for effective evaluation of ANIDS in the context of DoS and PROBE attacks.

The study also proposes a performance metric, GMAI in place of widely used ROC which proves to be a better metric. An expected cost model based on the opportunity cost concept which proves to be equivalent to GMAI is formulated. Hence, the GMAI can be treated as surrogate to service level for comparing alternative ANIDS.

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