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DOI: 10.1109/MILCIS.2015.7348942

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UNSW-NB15: A Comprehensive Data set for Network Intrusion Detection systems

(UNSW-NB15 Network Data Set)

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Abstract— One of the major research challenges in this field is the unavailability of a comprehensive network based data set which can reflect modern network traffic scenarios, vast varieties of low footprint intrusions and depth structured information about the network traffic. Evaluating network intrusion detection systems research efforts, KDD98, KDDCUP99 and NSLKDD benchmark data sets were generated a decade ago. However, numerous current studies showed that for the current network threat environment, these data sets do not inclusively reflect network traffic and modern low footprint attacks. Countering the unavailability of network benchmark data set challenges, this paper examines a UNSW-NB15 data set creation. This data set has a hybrid of the real modern normal and the contemporary synthesized attack activities of the network traffic. Existing and novel methods are utilised to generate the features of the UNSW-NB15 data set. This data set is available for research purposes and can be accessed from the link¹.

Keywords- UNSW-NB15 data set; NIDS; low footprint attacks; pcap files; tested

I. INTRODUCTION

Currently, due to the massive growth in computer networks and applications, many challenges arise for cyber security research. Intrusions /attacks can be defined as a set of events which are able to compromise the principles of computer systems, e.g. availability, authority, confidentiality and integrity [1]. Firewall systems cannot detect modern attack environments and are not able to analyse network packets in depth. Because of these reasons, IDSs are designed to achieve high protection for the cyber security infrastructure [2].

A Network Intrusion Detection System (NIDS) monitors network traffic flow to identify attacks. NIDSs are classified into misuse/signature and anomaly based [4]. The signature based matches the existing of known attacks to detect intrusions. However, in the anomaly based, a normal profile is created from the normal behavior of the network, and any deviation from this is considered as attack [3] [4]. Further, the signature based NIDSs cannot detect unknown attacks, and for these anomaly NIDS are recommended in many studies [4] [5].

The effectiveness of NIDS is evaluated based on their performance to identify attacks which requires a comprehensive data set that contains normal and abnormal behaviors [6]. Older benchmark data sets are KDDCUP 99 [7] and NSLKDD [8] which have been widely adopted for evaluating NIDS performance. It is perceived through several studies [6][9][10][11], evaluating a NIDS using these data sets does not reflect realistic output performance due to several reasons. First reason is the KDDCUP 99 data set contains a tremendous number of redundant records in the training set. The redundant records affect the results of detection biases toward the frequent records [10]. Second, there are also multiple missing records that are a factor in changing the nature of the data [9]. Third, The NSLKDD data set is the improved version of the KDDCUP 99, it tackles the several issues such as data unbalancing among the normal/abnormal records and the missing values [12]. However, this data set is not a comprehensive representation of a modern low foot print attack environment.

The above reasons have instigated a serious challenge for the cyber security research group at the Australian Centre for Cyber Security (ACCS)² and other researchers of this domain around the globe. Countering this challenge, this paper provides an effort in creating a UNSW-NB15 data set to evaluate NIDSs. The IXIA PerfectStorm tool³ is utilised in the Cyber Range Lab of the ACCS to create a hybrid of the modern normal and abnormal network traffic. The abnormal traffic through the IXIA tool simulates nine families of attacks that are listed in Table VIII. The IXIA tool contains all information about new attacks that are updated continuously from a CVE site⁴. This site is a dictionary of publicly known information security vulnerabilities and exposures. Capturing network traffic in the form of packets, the tcpdump⁵ tool is used. The simulation period was 16 hours on Jan 22, 2015 and 15 hours on Feb 17, 2015 for capturing 100 GBs. Further, each pcap file is divided into 1000 MB using the tcpdump tool. Creating reliable features from the pcap files, Argus⁶ and

¹ <http://www.cybersecurity.unsw.adfa.edu.au/ADFA%20NB15%20Datasets/>.

² <http://www.accs.unsw.adfa.edu.au/>

³ <http://www.ixiacom.com/products/perfectstorm>

⁴ <https://cve.mitre.org/>

⁵ <http://www.tcpdump.org/>

⁶ <http://qosient.com/argus/index.shtml>

Bro-IDS⁷ tools are utilised. Additionally, twelve algorithms are developed using a C# language to analyse in-depth the flows of the connection packets. The data set is labelled from a ground truth table that contains all simulated attack types. This table is designed from an IXIA report that is generated during the simulation period. The key characteristics of the UNSW-NB15 data set are a hybrid of the real modern normal behaviors and the synthetical attack activities.

The rest of the paper is organised as follows: section 2 examines the general goal and orientation of any IDS data set. Section 3 exposes in-detail the existing benchmark datasets shortcomings. The synthetic environment configuration and generation of UNSW-NB15 details are given in section 4. Section 5 is a comparative analysis between the KDDCUP99 and the UNSW-NB15 data set. Section 6 displays the final shape about the files of the UNSW-NB15 data set. Finally, section 7 concludes the work and future intentions.

II. THE GOAL AND ORIENTATION OF A NIDS DATA SET

A NIDS data set can be conceptualized as relational data [6]. Input to a NIDS is a set of data records. Each record consists of attributes of different data types (e.g., binary, float, nominal and integer) [6]. The label assigns each record of the data, either normal is 0 or abnormal is 1. Labelling is done by matching processed record, according to the particular NIDS scenario with the ground truth table of all transaction records.

III. CRITICISMS OF EXISTING DATA SETS

A quality of the NIDS data set reflects two important characteristics are a comprehensive reflection of contemporary threat and inclusive normal range of traffic. The quality of the data set ultimately affects the reliable outcome of any NIDS [6] [9]. In this section the disadvantages of existing data sets for NIDS are explored in the perspective of data set quality. The most widely adopted data sets for NIDS are KDDCUP99, and its improved version NSL-KDD.

A. KDDCup99 Data Set

Generating DARPA98 [13], (IST) group of Lincoln laboratories at MIT University performed a simulation with normal and abnormal traffic in a military network (U.S. Air Force LAN) environment. The simulation ended with nine weeks of raw tcpdump files. The training data size was about four GBs and consisted of compressed binary tcpdump files from seven weeks of network traffic. This was processed into approximately five million connection records. The simulation provided two weeks of test data which contained two million connection records [7] [13].

Upgrading DARAP98 network data features comprehensiveness, utilising the same environment (U.S. Air Force LAN), the simulation ended with 41 features for each connection along with the class label using Bro-IDS tool. The upgraded version of DARAP98 is referred to as KDDCUP99. In the KDDCUP99 data set, the whole extracted features were

divided into three groups of intrinsic features, content features and traffic features. Further, attack records in this data set are categorised into four vectors (e.g., DoS, Probe, U2R, and R2L). The training set of KDDCUP99 included 22 attack types and test data contained 15 attack types [13] [7].

A number of IDS researchers as have utilised these datasets due to their public availability. However, many researchers have reported majorly three important disadvantages of these datasets [6] [9] [10] [11] [12] which can affect the transparency of the IDS evaluation. First, every attack data packets have a time to live value (TTL) of 126 or 253, whereas the packets of the traffic mostly have a TTL of 127 or 254. However, TTL values 126 and 253 do not occur in the training records of the attack [9]. Second, the probability distribution of the testing set is different from the probability distribution of the training set, because of adding new attack records in the testing set [10][12]. This leads to skew or bias classification methods to be toward some records rather than the balancing between the types of attack and normal observations. Third, the data set is not a comprehensive representation of recently reported low foot print attack projections [11].

B. NSLKDD Data Set

According to [12] considering the three goals, an upgraded version of the KDD data set was created and it is referred to as NSLKDD. The first goal was, removing the duplication of the record in the training and test sets of the KDDCUP99 data set for the purpose of eliminating classifiers biased to more repeated records. Secondly, selecting a variety of the records from different parts of the original KDD data set is to achieve reliable results from classifier systems. Third, eliminating the unbalancing problem among the number of records in the training and testing phase is to decrease the False Alarm Rates (FARs). The major disadvantage of NSLKDD is that, it does not represent the modern low foot print attack scenarios [9] [12].

IV. UNSW-NB15 DATA SET

In this section, the synthetic environment configuration and generation of UNSW-NB15 details are presented. The section includes mainly the testbed configuration details and the whole processes which involved in generating UNSW-NB15 from the configured testbed.

A. An IXIA tool Testbed Configuration

According to Fig. 1, the IXIA traffic generator is configured with the three virtual servers. The servers 1 and 3 are configured for normal spread of the traffic while server 2 formed the abnormal/malicious activities in the network traffic. Establishing the intercommunication between the servers, acquiring public and private network traffic, there are two virtual interfaces having IP addresses, *10.40.85.30* and *10.40.184.30*. The servers are connected to hosts via two routers. The router 1 has *10.40.85.1* and *10.40.182.1* IP addresses, whereas router 2 is configured with *10.40.184.1* and

⁷ <https://www.bro.org/index.html>

10.40.183.1 IP addresses. These routers are connected to the firewall device that is configured to pass all the traffic either normal or abnormal. The tcpdump tool is installed on the router 1 to capture the Pcap files of the simulation uptime. Moreover, the central intent of this whole testbed was to capture the normal or abnormal traffic, which was originated from the IXIA tool and dispersed among network nodes (e.g., servers and clients). Importantly, the IXIA tool is utilised as an attack traffic generator along with as normal traffic, the attack behaviour is nourished from the CVE site for the purpose of a real representation of a modern threat environment.

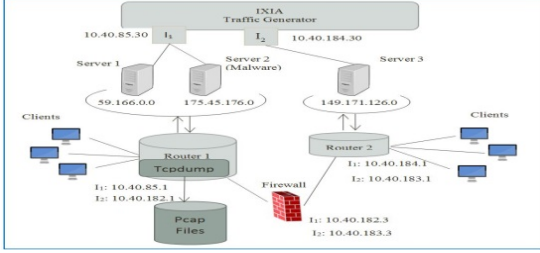


Figure 1. The Testbed Visualization for UNSW-NB15

Due to the speed of network traffic and the way of exploiting by modern attacks, the IXIA tool is configured to generate one attack per second during the first simulation to capture the first 50 GBs. On the other hand, the second simulation is configured to make ten attacks per second to extract another 50 GBs.

B. Traffic Analysis

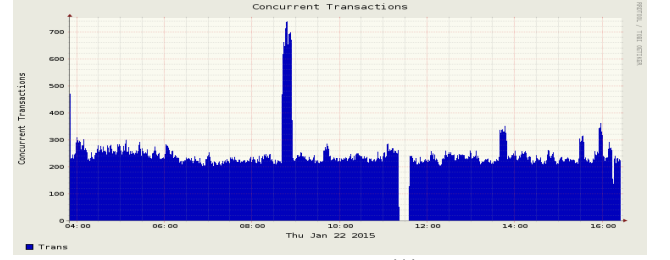
The traffic analysis is described for the cumulative flows during the period of the simulation while generating the UNSW-NB15 data set. In Table I, the data set statistics are provided which represents the simulation period, the flows numbers, the total of source bytes, the destination bytes, the number of source packets, the number of destination packets, protocol types, the number of normal and abnormal records and the number of unique source/destination IP addresses.

TABLE I. DATA SET STATISTICS

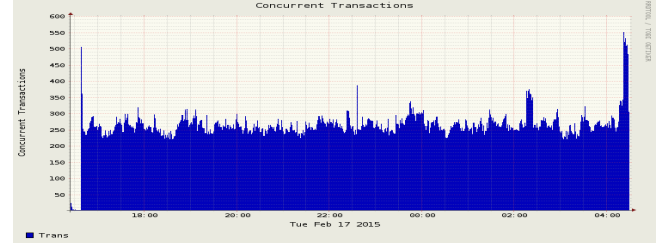
Statistical features		16 hours	15 hours
No._of_flows		987,627	976,882
Src bytes		4,860,168,866	5,940,523,728
Des bytes		44,743,560,943	44,303,195,509
Src Pkts		41,168,425	41,129,810
Dst pkts		53,402,915	52,585,462
Protocol types	TCP	771,488	720,665
	UDP	301,528	688,616
	ICMP	150	374
	Others	150	374
Label	Normal	1,064,987	1,153,774
	Attack	22,215	299,068
Unique	Src ip	40	41
	Dst ip	44	45

In Fig. 2, the concurrent transactions with respect the time which are presented during the 16 hours of the simulation on Jan 22, 2015 and the 15 hours of Feb 17, 2015. The x-axis shows the time of each 10 seconds and the y-axis represents

the number of Kbytes that is sniffed during each simulation period.



(A)



(B)

Figure 2. The Concurrent Transactions of Flows during the Simulation Periods.

C. Architectural Framework

The whole architecture which is involved in generating the final shape of the UNSW-NB15 from pcap files to CSV files with 49 features (attributes in any CSV file) is presented in Fig. 3. All the 49 features of the UNSW-NB15 data set are elaborated from Tables II-VII along with the generation sequence explanation for understanding convenience.

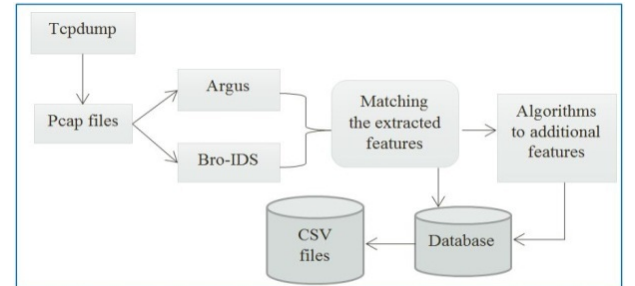


Figure 3. Framework Architecture for Generating UNSW-NB15 data set

When the simulation was running on the testbed presented in Fig. 1, the pcap files are generated by using the tcpdump tool. The features of the UNSW-NB15 data set are extracted by using Argus, Bro-IDS tools and twelve algorithms are developed using c# programming language as shown in Fig. 3. Moreover, these features are matched according to the equal flow features as listed in Table II. These tools are installed and are configured on Linux Ubuntu 14.0.4. The detailed formatting description of the UNSW-NB15 data set is elaborated in the following sections.

D. The extracted features from the Argus and Bro-IDS Tools

Argus tool processes raw network packets (e.g., pcap files) and generates attributes/features of the network flow packets. The Argus tool consists of an Argus-server and Argus-clients.

The Argus-server writes pcap files of receiving packets in Argus files in the binary format. The Argus clients extract the features from the Argus files.

Bro-IDS tool is an open-source network traffic analyser. It is predominantly a security monitor that inspects all network traffic against malicious activities. The Bro-IDS tool is configured to generate three log files from the pcap files. First, the conn file records all connection information seen on the pcap files. Second, the http file includes all HTTP requests and replies. Third, the ftp file records all activities of a FTP service.

Finally, the output files of the two different tools, Argus and Bro-IDS are stored in the SQL Server 2008⁸ database to match the Argus and Bro-IDS generated features by using the flow features as reflected in Table II.

TABLE II. FLOW FEATURES

#	Name	T.	Description
1	<i>srcip</i>	N	Source IP address
2	<i>sport</i>	I	Source port number
3	<i>dstip</i>	N	Destination IP address
4	<i>dport</i>	I	Destination port number
5	<i>proto</i>	N	Transaction protocol

E. The matched features of the Argus and Bro-IDS Tools

These features include a variety of packet-based features and flow-based features. The packet based features assist the examination of the payload beside the headers of the packets. On the contrary, for the flow based features and maintaining low computational analysis instead of observing all the packets going through a network link, only connected packets of the network traffic are considered. Moreover, the flow-based features are based on a direction, an inter-arrival time and an inter-packet length [6] (mentioned in Tables III and IV, as well as they are executed in the connection features of Table VI). The matched features are categorised into three groups: Basic, Content, and Time which were described in Tables III, IV and V, respectively.

TABLE III. BASIC FEATURES

#	Name	T	Description
6	<i>state</i>	N	The state and its dependent protocol, e.g. ACC, CLO, else (-)
7	<i>dur</i>	F	Record total duration
8	<i>sbytes</i>	I	Source to destination bytes
9	<i>dbytes</i>	I	Destination to source bytes
10	<i>sttl</i>	I	Source to destination time to live
11	<i>dttl</i>	I	Destination to source time to live
12	<i>sloss</i>	I	Source packets retransmitted or dropped
13	<i>dloss</i>	I	Destination packets retransmitted or dropped
14	<i>service</i>	N	http, ftp, ssh, dns ...else (-)
15	<i>sload</i>	F	Source bits per second
16	<i>dload</i>	F	Destination bits per second
17	<i>spkts</i>	I	Source to destination packet count
18	<i>dpkts</i>	I	Destination to source packet count

⁸ <http://www.microsoft.com/en-au/download/details.aspx?id=26113>

Importantly, the features from 1-35 represent the integrated gathered information from data packets. The majority of features are generated from header packets as reflected in Tables II-V. It is acknowledged that the UNSW-NB15 data set creates additional flow based features as described in the following section.

TABLE IV. CONTENT FEATURES

#	Name	T	Description
19	<i>swin</i>	I	Source TCP window advertisement
20	<i>dwin</i>	I	Destination TCP window advertisement
21	<i>stcpb</i>	I	Source TCP sequence number
22	<i>dtcpb</i>	I	Destination TCP sequence number
23	<i>smeansz</i>	I	Mean of the flow packet size transmitted by the src
24	<i>dmeansz</i>	I	Mean of the flow packet size transmitted by the dst
25	<i>trans_depth</i>	I	the depth into the connection of http request/response transaction
26	<i>res_bdy_len</i>	I	The content size of the data transferred from the server's http service.

TABLE V. TIME FEATURES

#	Name	T	Description
27	<i>sjit</i>	F	Source jitter (mSec)
28	<i>djit</i>	F	Destination jitter (mSec)
29	<i>stime</i>	T	record start time
30	<i>ltime</i>	T	record last time
31	<i>sintpkt</i>	F	Source inter-packet arrival time (mSec)
32	<i>dintpkt</i>	F	Destination inter-packet arrival time (mSec)
33	<i>tcprtt</i>	F	The sum of 'synack' and 'ackdat' of the TCP.
34	<i>synack</i>	F	The time between the SYN and the SYN_ACK packets of the TCP.
35	<i>ackdat</i>	F	The time between the SYN_ACK and the ACK packets of the TCP.

F. The additional features from the matched features

The generation details of the twelve additional features of the UNSW-NB15 data set (e.g., Table VI) from the matched features (e.g., Tables II-IV) are provided. Table VI is divided into two parts according to the nature and purpose of the additional generated features. The features from 36-40, are considered as general purpose features whereas from 41-47, are labelled as connection features. In the general purpose features, each feature has its own purpose, according to the defence point of view, whereas connection features are solely created to provide defence during attempt to connection scenarios. The attackers might scan hosts in a capricious way. For example, once per minute or one scan per hour [12]. In order to identify these attackers, the features 36-47 of Table VI are intended to sort accordingly with the last time feature to capture similar characteristics of the connection records for each 100 connections sequentially ordered.

TABLE VI. ADDITIONAL GENERATED FEATURES

#	Name	T	Description
General purpose features			
36	<i>is_sm_ips_ports</i>	B	If source (1) equals to destination (3)IP addresses and port numbers (2)(4) are equal, this variable takes value 1 else 0

37	<i>ct_state_ttl</i>	I	No. for each state (6) according to specific range of values for source/destination time to live (10) (11).
38	<i>ct_flw_http_mthd</i>	I	No. of flows that has methods such as Get and Post in http service.
39	<i>is_fip_login</i>	B	If the ftp session is accessed by user and password then 1 else 0.
40	<i>ct_fip_cmd</i>	I	No of flows that has a command in ftp session.
Connection features			
41	<i>ct_srv_src</i>	I	No. of connections that contain the same service (14) and source address (1) in 100 connections according to the last time (26).
42	<i>ct_srv_dst</i>	I	No. of connections that contain the same service (14) and destination address (3) in 100 connections according to the last time (26).
43	<i>ct_dst_ltm</i>	I	No. of connections of the same destination address (3) in 100 connections according to the last time (26).
44	<i>ct_src_ltm</i>	I	No. of connections of the same source address (1) in 100 connections according to the last time (26).
45	<i>ct_src_dport_ltm</i>	I	No of connections of the same source address (1) and the destination port (4) in 100 connections according to the last time (26).
46	<i>ct_dst_sport_ltm</i>	I	No of connections of the same destination address (3) and the source port (2) in 100 connections according to the last time (26).
47	<i>ct_dst_src_ltm</i>	I	No of connections of the same source (1) and the destination (3) address in in 100 connections according to the last time (26).

G. The labelled features

To label this data set, the IXIA tool has generated report about the attack data. This report is configured in the shape of the ground truth table to match all transaction records. This table consists of eleven attributes, e.g. (start time, last time, attack category, attack subcategory, protocol, source address, source port, destination address, destination port, attack name and attack reference). This data set is labelled as listed in Table VII, attack categories (i.e., *attack_cat*) and *label* for each record either 0 if the record is normal and 1 if the record is attack.

TABLE VII. LABELLED FEATURES

#	Name	T	Description
48	<i>attack_cat</i>	N	The name of each attack category. In this data set, nine categories (e.g., Fuzzers, Analysis, Backdoors, DoS, Exploits, Generic, Reconnaissance, Shellcode and Worms)
49	<i>Label</i>	B	0 for normal and 1 for attack records
Type (T): N: nominal, I: integer, F: float, T: timestamp and B: binary			

V. DATA SET RECORDS DISTRIBUTION

Table VIII represents the distribution of all records of the UNSW-NB15 data set. The major categories of the records are normal and attack. The attack records are further classified into nine families according to the nature of the attacks.

TABLE VIII. DATA SET RECORD DISTRIBUTION

Type	No. Records	Description
Normal	2,218,761	Natural transaction data.
Fuzzers	24,246	Attempting to cause a program or network suspended by feeding it the randomly generated data.
Analysis	2,677	It contains different attacks of port scan, spam and html files penetrations.
Backdoors	2,329	A technique in which a system security mechanism is bypassed stealthily to access a computer or its data.
DoS	16,353	A malicious attempt to make a server or a network resource unavailable to users, usually by temporarily interrupting or suspending the services of a host connected to the Internet.
Exploits	44,525	The attacker knows of a security problem within an operating system or a piece of software and leverages that knowledge by exploiting the vulnerability.
Generic	215,481	A technique works against all block-ciphers (with a given block and key size), without consideration about the structure of the block-cipher.
Reconnaissance	13,987	Contains all Strikes that can simulate attacks that gather information.
Shellcode	1,511	A small piece of code used as the payload in the exploitation of software vulnerability.
Worms	174	Attacker replicates itself in order to spread to other computers. Often, it uses a computer network to spread itself, relying on security failures on the target computer to access it.

VI. COMPARISON OF THE KDDCUP99 AND UNSW-NB15 DATA SET

Table IX shows a comparative analysis among the KDDCUP99 and UNSW-NB15 data sets. The table consists of eight parameters are the number of networks, number of unique ip address, type of data generation, duration of the data generation and its output format, attack vectors and the tools that are used to extract the features and the number of features for each data set. It can be observed that UNSW-NB15 data set has different attack families which ultimately reflect modern low foot print attacks.

TABLE IX. COMPARISON OF KDD CUP 99 AND UNSW-NB15

#	Parameters	KDDCUP99 [7]	UNSW-NB15
1	No. of networks	2	3
2	No. of distinct ip address	11	45
3	Simulation	Yes	Yes
4	The duration of data collected	5 weeks	16 hours 15 hours
5	Format of data collected	3 types (tcpdump, BSM and dump files)	Pcap files
6	Attack families	4	9
7	Feature Extraction tools	Bro-IDS tool	Argus, Bro-IDS and new tools.
8	No. of features extraction	42	49

VII. FINAL SHAPE OF THE UNSW-NB15 DATA SET FILES

In this section, the description of the final shape of the UNSW-NB15 is provided. The purpose of this section is to guide the researchers on how to use and manipulate final CSV files of the UNSW-NB15 data set. Four CSV files of the data records are provided and each CSV file contains attack and normal records. The names of the CSV files are *UNSW-NB15_1.csv*, *UNSW-NB15_2.csv*, *UNSW-NB15_3.csv* and *UNSW-NB15_4.csv*.

In each CSV file, all the records are ordered according the last time attribute. Further, the first three CSV files each file contains 700000 records and the fourth file contains 440044 records. The ground truth table is named *UNSW-NB15_GT.csv*. The list of event file is labelled *UNSW-NB15_LIST_EVENTS* which contains attack category and subcategory. The interested reader can obtain the raw pcap files by e-mailing the authors.

VIII. CONCLUSION AND FUTURE WORK

In this paper, the existing benchmark datasets are not representing the comprehensive representation of the modern orientation of network traffic and attack scenarios. UNSW-NB15 is created by establishing the synthetic environment at the UNSW cyber security lab. The key utilised IXIA tool, has provided the capability to generate a modern representative of the real modern normal and the synthetical abnormal network traffic in the synthetic environment. UNSW-NB15 represents nine major families of attacks by utilising the IXIA PerfectStorm tool. There are 49 features that have been developed using Argus, Bro-IDS tools and twelve algorithms which cover characteristics of network packets. In contrast the existing benchmark data sets such as KDD98, KDDCUP99 and NSLKDD, realised a limited number of attacks and information of packets which are outdated. Moreover, the UNSW-NB15 is compared with KDDCUP99 data set by considering some key features and it shows the benefits. In future, it is expected that, the UNSW-NB15 data set can be helpful to the NIDS research community and considered as a modern NIDS benchmark data set.

ACKNOWLEDGMENT

This work is supported by cyber range lab of the Australian Centre for Cyber Security (ACCS) at UNSW in Canberra. The authors are grateful for the manager of the Cyber range lab.

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