Combinatorial Optimization based Feature Selection Method: A study on Network Intrusion Detection

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Abstract

Advancements in computer networks and communication technologies like software defined networks (SDN), Internet of things (IoT), microservices architecture, cloud computing and network function virtualization (NFV) have opened new fronts and challenges for security experts to combat against modern cyberattacks. Relying on perimeter defense and signature-based network security solutions like Intrusion Detection and Prevention Systems (IDS/IPS) have failed to deliver adequate level of security against new attack vectors such as advance persistent threats, zero days, ransomware, botnets and other forms of targeted attacks. Recent developments in machine learning and cognitive computing have shown great potential to detect unknown and new intrusion events where legacy misuse and anomaly based intrusion detection systems usually fail. In this research study we applied state of the art machine learning algorithms on UNSW-NB15 dataset for potential applicability to detect new attacks. We also proposed a novel wrapper based feature selection technique TS-RF using metaheuristic Tabu Search (TS) algorithm and Random Forest (RF) ensemble classifier. Results obtained by applying proposed feature selection technique i.e. TS-RF on UNSW-NB15 dataset show improvement in overall intrusion detection accuracy while it reduces computation complexity as it removes more than 60\% features.

Keywords: Intrusion detection, computer networks, machine learning, feature selection, metaheuristics

1. Introduction

The Internet has revolutionized the world and helped to make it global village in real sense. Its exponential growth allows us to interconnect and communicate anywhere, anytime and access various services. This has become possible due to the advancements in network technologies, economical access of services and availability of new products and devices. But the advancement and growth of Internet has opened new challenges and problems for researchers and practitioners working continuously for its improvement. Security, privacy and trust in the Internet is one of the biggest challenge faced not only by industries, government organizations etc., but also for a common user.

Internet is a public network, which is open and used by all \cite{1}. There is deafening increase in the numbers of cyberattacks performed every year. In computers and computer networks an attack is any attempt to expose, alter, disable, destroy, steal or gain unauthorized access to or make unauthorized use of an Asset \cite{2}. Main findings on cyberattacks statistics published by Symantec Internet Security Threat Report (ISTR) 2018 \cite{3} are given below:

1. 92\% increase in new Malware variants in 2017, where Malware or malicious software is any program or file which is harmful to a computer.
2. 600\% increase in the number of attacks since 2016 against devices and sensors connected to Internet. Devices, sensors, actuators connected to Internet to share their statuses and take instructions from the server are usually known as Internet of things (IoT).
3. 54% increase in the mobile Malware variants.
4. 45% increase in the new Ransomware and 13% increase in the number of reported vulnerabilities (any weakness in the system, software or process). Ransomware is a type of malicious software that threatens to publish the victim’s data or perpetually block access to it unless a ransom is paid. It has gain more visibility after the widespread of Ransomware name WannaCry in May 2017 [4].

Gaining unauthorized access of systems, resources or communications for malicious intent is not new. Such notable incidents dated back to World War II era [5]. As discussed earlier, due to the ubiquitousness of new affordable technologies cybercrimes have gained significant momentum. This wild growth of cybercrimes have different reasons and motivations. Taylor [6] discussed several reasons and Brewster et al. presented attack motivations taxonomy in [7]. They discussed many motivations like political, ideological, commercial, emotional, financial, personal, etc, which can be behind a cyberattack.

Main reason and motivations for launching cyberattacks are:

1. Political or social cause: different incidents have been reported where hackers interfere to influence social or a political cause. A. Bessi, E. Ferrara [8], B. Kollanyi et.al [9] and H. Allcott and M. Gentzkow [10] discussed and explained how social bots distort 2016 US Presidential Election online discussion. Such hacking activities and groups of hackers are usually sponsored by the state or the competitors of the target organization. [11].
2. Easy and control free availability of tools: basic but often neglected reason of increase numbers of cyberattacks is the easy and control free availability of tools and procedures used by hackers. As a result, a user can easily launch an attack without requiring a detail and technical understanding of the underlying technologies and infrastructure. Hansman [12] discussed that attack sophistication has been increased and intruder knowledge or skills which are required to perpetuate an attacks has been reduced over years.
3. Financial gain: Ransomware is the most common type of cyberattack used for obtaining financial gains.

With these numbers and severity of attacks traditional security solutions like Anti-Virus (AV), firewalls, Intrusion Detection Systems (IDS) etc. have been questioned for their reliability in detecting and providing safeguard against advance attacks. Antivirus (AV) can only block and stop the execution of any malicious or un-wanted program on the hosts. They usually work on the principle of signatures or patterns of bad programs or executables. A virus signature is a continuous sequence of bytes that is common for a certain malware sample [13].

Conventional firewalls can only allow and deny traffic on the basis of Open system Interconnection (OSI) [14] - network layer IP Addresses [15] and transport layer port numbers [15], they are usually known as stateful firewalls. They cannot perform deep packet inspection (DPI) [16] to inspect and look inside the packets for any kind of intrusions or malware.

With the advent of unified threat management (UTM) [17] and next generation based firewalls (NGFW) [18], firewalls can now look beyond packet headers. They can inspect and filter traffic on the basis of payload. Payload is actual message or data generated by the source machine for its intended recipient. These firewalls are also known as application and user aware firewalls because they can detect applications or protocols streams following through them and allow security administrators to apply policies on the basis of applications or users instead of fixed port numbers and IP Addresses. They also have built-in mechanism to detect intrusions.

Karen and Mell [19] defines intrusion detection is the process of monitoring the events occurring in a computer system or network and analyzing them for signs of possible incidents, which are violations or imminent threats of violation of computer security policies, acceptable use policies, or standard security practices. Furthermore, the Intrusion Prevention System (IPS) is a system that has all the capabilities of an IDS, and it can attempt to block possible incidents [20].

In this paper we proposed a new wrapper based feature selection method which is based on Tabu Search (TS) metaheuristic optimization algorithm [21, 22]. For discussion on different feature selection methods refer Section 6. We used TS for feature search while Random Forest as a learning method. Results discussed
in section 6.3 show that TS outperformed all other feature selection method by improving classifier accuracy sufficiently at reduced feature space by 60%.

Rest of the paper is organized as follows. Section 2 presents details related to Intrusion Detection Systems (IDS). Section 3 presents review of legacy and recent IDS datasets. Section 4 discussed UNSW-NB15 dataset at length. Section 5 discussed machine learning algorithms used in our study and their findings. Section 6 discussed different feature selection methods studied and applied in our paper followed by the results obtained from TS-RF, conclusion and future directions.

2. An Overview of Intrusion Detection Systems (IDS)

An Intrusion Detection Prevention System (IDS, IPS) plays an integral role to strengthen the security posture of an organization. Historically, an IDS is categorized as anomaly-based and misuse-based. Misuse-based IDS is also known as signature based IDS. However, modern IDS can be classify based on different parameters discussed below [23].

1. Detection Methodologies
2. Detection Approach
3. Analysis Target
4. Reaction on Intrusion Event
5. Analysis Timing
6. Architecture

2.1. Detection Methodologies

Liao [23] and Scarfone [19] defines three different intrusion detection methodologies. These are: Signature-based Detection (SD), Anomaly-based Detection (AD) and Stateful Protocol Analysis (SPA) based detection methodologies. We will discuss detection methods in more detail because these are the core components of any IDS.

2.1.1. Signature-based IDS

A signature based intrusion detection system uses intrusion signatures to detect intrusions. An intrusion signature is a pattern or string that corresponds to known attack or threat. Signature-based intrusion detection systems have huge database of known attacks or threats. They monitor every packet flowing through the network or system’s activity and try to compare it with signature database. If a signature is matched then they trigger an appropriate alert. On the basis of generated alert, the prevention engine may block that intrusion activity. Signature-based IDS are also known as knowledge-based or misuse-based IDS. The examples of signature based IDS are Snort, Suricata [24]. Signature-based detection has shown promising results to detect known threats but it is proved ineffective at detecting novel or new type of threats or intrusions, because they do not have signatures for them.

2.1.2. Anomaly-based IDS

Anomaly-based intrusion detection systems (AD) use anomalies to detect intrusions. An anomaly can be considered as deviation from the known behavior. Anomaly-based IDS first build profiles or develop a model of normal or expected behavior of the system, it is also called baseline. Profiles are usually build using continuous monitoring or training of the system over a period of time. When profile building process is completed then IDS is deployed to detect intrusions, based on the deviations from the baseline or what it had learn during the training period [25].

The main benefit of anomaly-based IDS is the their potential to detect unknown or novel attacks. However one of the biggest challenge of anomaly based IDS is False Positive Rate (FPR). Anomaly-based IDS are prone to generate high false positives because of any benign activity that deviates significantly from profiles will lead to generate false alarm.
Table 1: Pros and Cons of Intrusion Detection Methodologies

| Signature-based | Anomaly-based | Stateful Protocol Analysis |
|-----------------|---------------|----------------------------|
| **Pros**        | **Pros**      | **Pros**                   |
| • Simplest & effective detection methodology | • Effective to detect new and unforeseen vulnerabilities and attacks. | • Efficient at detecting protocol design level vulnerabilities and flaws. |
| • High detection rate with less false positive | • Facilitate the detection of variant of attacks | • Can distinguish unexpected sequence or protocol dialogs. |
| • Provide more granular contextual analysis of attack(s) | | |
| **Cons**        | **Cons**      | **Cons**                   |
| • Ineffective to detect unknown (new) attacks, evasion attacks, and variants of known attacks | • Difficult to build accurate model or profile | • Resource hungry method |
| • Difficult to maintain signature database up to date | • Requires significant training time | • Limited capabilities to detect OS or API level attacks |

2.1.3. Stateful Protocol Analysis-based IDS

Stateful protocol analysis-based IDS can perform Deep Packet Inspection (DPI) to compare protocol deviations from the predetermined or standard profiles of generally accepted definitions of normal protocol activities [19]. DPI refers to the capability to look inside the packets’ payload. The stateful refers to the fact that these IDS can understand various protocol dialogs and their hand-shaking processes [26]. These IDS can also detect unexpected sequences of commands during connection establishment process. Thus it makes an IDS capable to detect and block intrusions at protocol level.

A main benefit of stateful protocol analysis-based IDS is they show good detection against the specific inherent vulnerabilities exist in the protocols’ design or its structure. However, they are very resource-intensive because of the complexity of the analysis and overhead involved in performing “state” tracking. State tracking is a process in which IDS keeps track of type and state information of the protocol dialogs or messages exchanged between sender and receiver. Comparison of all three detection methodologies are presented in Table 1.

2.2. Detection Approaches

Liao [23] classify intrusion detection systems in five different classes. The basic classification criteria is their characteristics and detection techniques which are discussed below.

2.2.1. Statistics-based

Statistics-based intrusion detection approach uses different statistical methods like Baye’s theorem [27], probability, mean, standard deviation etc. to identify abnormal behavior. They build a model or profile of normal and malicious activities of traffic and calculate the probability of the new events to correctly classify it.
2.2.2. Pattern-based

Pattern-based detection techniques focus on patterns of known attacks through string matching, regular expression and pattern recognition. They are very similar to signature based IDS discussed in section 2.1.1.

2.2.3. Rule-based

A simple rule based approach works on the principle of if-else conditions matching. For example, if an internal host is trying to establish a connection with an external server, the IDS will first check and verify the reputation of the Internet Protocol (IP) address or domain name of the target machine, if the domain name is blacklisted at Domain Name System based Blackhole List (DNSBL) [28] or Real-time Blackhole List (RBL) [29] or other reputation based databases, the connection attempt should be blocked.

2.2.4. State-based

State-based detection methods exploit the behavior of finite state machine [30]. They continuously monitor and keep tracks of machines’ states in terms of sessions, packets in and out, number of connections to specific host or IP address etc. Once they establish a state-transition maps or state tables of active connections, they can look for any possible intrusions.

2.2.5. Heuristics-based

Heuristic are used to find quality solution within reasonable time frame. Heuristic based detection approaches are usually inspired from biological behavior of different animals or birds and artificial intelligence [31].

2.3. Analysis Target

Analysis target dictates the prime purpose of the IDS being used. Based on what they can inspect or monitor, where they can be deployed and what sort of potential malicious activities they can detect and block, we can further divide IDS into different analysis target sub-classes. These are discussed and described below.

1. Network-based IDS (NIDS)
2. Host-based IDS (HIDS)
3. Application-based IDS (AIDS)
4. Wireless-based IDS (WIDS)
5. Network Behavior Analysis (NBA) based IDS
6. Mixed IDS (MIDS)

2.3.1. Network-based IDS (NIDS)

Network based intrusion detection systems usually deployed at network transit points where most of the network traffic is passed [32]. The core principle of network based IDS is to monitor network traffic and looks for possible intrusions by exploiting different methodologies and approaches discussed in Section 2.1 and 2.2.

2.3.2. Host-based IDS (HIDS)

Host based intrusion detection systems actively monitors hosts activities for any potential malicious activity [33, 34]. It includes hosts’ process tables, network connections (ins and outs), registry entries, filesystem activities, prefetch items etc. and try to analyze their behavior for any signs of abnormality.

2.3.3. Wireless-based IDS (WIDS)

Wireless-based IDS is very similar to network-based IDS (NIDS), but it captures wireless network traffic, such as wireless ad-hoc networks, Wireless Sensor Networks (WSN), wireless mesh networks, Wireless Body Area Networks (WBAN) etc. [35].
2.3.4. Network Behavior Analysis (NBA) based IDS

Network Behavior Analysis (NBA) based IDS inspects network traffic to recognize attacks with unexpected traffic flows. For example, it tries to detect Denial of Service (DoS) attack, certain type of malware, backdoors etc. [36]. NBA based IDS usually have a set of sensors deployed at different network segments and a console for central reporting and monitoring of network alerts.

2.3.5. Mixed or Hybrid IDS (MIDS)

Mixed or hybrid IDS can incorporate different family of IDS discussed above. It provides more detail and accurate detection and prevention against attacks [36]. Hybrid IDS solutions actually mitigate the weakness and limitations of one another. Adopting multiple technologies as MIDS can fulfill the goal for a more complete and accurate detection.

2.4. Reaction on Intrusion Events

IDS can be classified based on how they respond to an intrusion event and there are two ways to do that which are discussed below.

2.4.1. Passive

Passive IDS only generates alerts or notifications when it encounter any intrusion event.

2.4.2. Active

On the other hand, active IDS have capabilities to take some actions based on the type of intrusion. For example, it can terminate live streams by sending RESET packets, covering holes, shutdown services, and start logging an intruder.

2.5. Analysis Timing

IDS can be classified based on how their analysis engine works. Analysis engine is the core component of any IDS. When IDS receives a packet from different streams or it monitors host activities then those activities or traffic must be analyzed in order to detect possible intrusions. Analysis engine actually apply different methodologies and detection techniques discussed in Sections 2.1 and 2.2 to detect true intrusions.

Event analysis is usually performed in two ways (i) online real-time analysis of events and (ii) periodic online or offline analysis.

2.5.1. Online real-time analysis of events

Online real-time analysis engine detects intrusions in real-time mode. NIDS receives network traffic from different sources (uplink, downlink) streams and analyze the traffic on the fly as they receive it. Online realtime analysis engine demands extreme computational power to process high traffic volume to generate useful alerts in timely manner.

2.5.2. Periodic online or offline analysis

Periodic online or offline analysis engine does not operate in real-time mode. Rather the analysis engine is invoked on periodic intervals, performs analysis for fixed time interval. Periodic offline engines work on collected historical network or host activities. These analysis timing do not require high computational power, however the biggest draw back of periodic online analysis engine is that it can miss real intrusion events.
3. Review of IDS Datasets

In this research paper we apply different state of the art Machine Learning (ML) algorithms which are discussed in Section 5. ML is a branch of Artificial Intelligence (AI) that deals with the study of algorithms and statistical models to empower machines to learn and take smart decisions. Any ML based algorithm requires dataset to build that model. So in this section we will present a brief overview of different available IDS datasets.

Dataset plays a crucial role in the performance evaluation and testing of any IDS. There are different IDS datasets which have been proposed in last two decades [37]. Usually a dataset consists of number of attributes known as input vector or feature vector and an output (class label) see Section 5 for details. For the purpose of understanding we have divided the datasets into two categories i.e. Legacy datasets and Recent datasets.

3.1. Legacy Datasets

All those datasets which are created and proposed between 1998 and 2008 are grouped into legacy datasets.

3.1.1. DARPA Datasets (1998-99)

MIT Lincoln lab built two datasets which are known as DARPA’98 & ’99 [38] datasets. DARPA’98 and DARPA’99 datasets consist of several weeks of network traffic captured by using tcpdump [39] tool ( a utility which is used to capture packets from the network). Captured network traffic data is later stored in Packet CAPture files generally known as PCAP files. These dataset faced serious limitations such as (i) existence of duplicated records (ii) Unbalanced samples of normal and attack traffic classes and (iii) comprises of synthetic traffic only. Traffic simulated with the help of a software or a hardware to emulate the behavior of a real user is known as synthetic traffic.

3.1.2. KDDCup99 dataset (1999)

Stolfo et al. [40, 41] built the dataset for Knowledge Discovery Contest’ 99 (KDD’99) contest. It was inherited from DARPA’98 dataset having 41 features. KDD’99 dataset consists of four main attack categories which are Denial of Service (DoS), User to Root (U2R), Remote to Local (R2L) and Probing Attacks. Training set consists of 24 variants of these attacks while 14 different attack variants are present in test data only.

3.1.3. NSL-KDD Dataset (2000)

Tavallaee et al. [42] discovered that KDDCup’99 dataset has some serious weaknesses (i) large number of redundant records (ii) low difficulty level of records in the dataset, etc. Tavallaee et al. enhanced the KDDCup’99 dataset by developing NSL-KDD dataset. From the original dataset, they removed a large number of duplicated records, and applied a methodology to improve the record’s difficulty level in the dataset.

3.1.4. DEFCON Datasets (2002)

DEFCON-8 dataset was developed in 2000. It contains port scanning and buffer overflow attacks only. DEFCON-10 dataset was created in 2002. It contains network traffic captured during a hacking competition known as Capture The Flag (CTF). Hackers were divided into blue team (defenders) and red team (attackers). The traffic produced during CTF is very different from real world network traffic since it contains mostly intrusive traffic without any normal background traffic. Due to this limitation, DEFCON dataset has been found useful only in evaluating alert correlation techniques [43].
3.2. Recent Datasets

As discussed in Section 1 threat landscape is totally changed over last few years. So researchers developed new datasets to address and incorporate new types of attacks like botnet, ransomware etc. and to collect traffic that is more realistic and similar to modern user behavior. Botnet is an overlay covert channel used to communicate and control infected hosts on the Internet [44]. Some of the notable datasets published in last decade are briefed in this section.

3.2.1. Sperotto (2008)

Sperotto et al. [45] created a flow based IDS dataset in 2008. Sperotto dataset is labeled real traffic. The main issue with this dataset is that the amount of traffic collected, which is very low and the network topology is very simple. They only monitor a single host (honeypot) connected to a university campus network. A honeypot is a network-attached decoy system exploited to attract attackers and to detect, deflect or study their hacking tactics [46]. Authors claim that dataset volume is sufficient for IDS study however they merely collected 6 days of traffic, which is not sufficient to study and test new type of attacks and their variants based on daily and weekly traffic evolution patterns.

Labeling of the dataset is also questionable. Labeling is performed based on the logs collected from the honeypot system, what makes it dependable on the detection system configuration and the log processing.

3.2.2. MAWI Working Lab Dataset (2010)

This dataset is contributed by MAWILab [47] (Measurement and Analysis on the WIDE Internet) since from 2010. It contains set of labeled traffic in the MAWI archive (sample points B and F). The archive contains daily traffic of 15 minutes captured in a link between Japan and the United States. Although the archive contains traces since 2001 but only the traffic since 2007 is labeled. The labels are generated by using a combination of several anomaly detection classifiers. This dataset is really extensive and allows the analysis for a very long period. The main limitation is that the trace is obtained only during a 15 minutes period per day. In addition, the labeling is dependent on the classifiers that have been used in the process and their generation of false positives.

3.2.3. UNB ISCX2012 (2012)

This dataset was created by Shiravi et al. [48]. The notable contribution of this dataset is the use of traffic profiles (i.e. $\alpha$&$\beta$) for the traffic generation. The authors define $\alpha$ profiles for attack traffic and $\beta$ profiles for background (normal) traffic. They developed and tested their idea in a network consists of 17 Windows XP workstations and a single Windows 7 computer. They collected data for 7 days. The main drawbacks of this dataset nowadays are its reduced duration, the use of somehow old operating systems WindowsXP, and the use of synthetic traffic.

3.2.4. CTU-13 (2013)

This dataset is presented in [25]. It contains traffic of 13 different malware captures in a real network environment. The traffic flows consists of labeled botnet, normal and background traffic. Here background traffic means the authors are not really able to decide if it is malicious activity or not. For privacy reasons, pcap files are only offered when no information about the network is present, e.g. a single host with synthetic traffic, however flow traces are available in several formats.

The main limitation of this dataset is the capture duration which is short duration of the traces, that impedes building models that consider cyclostationary evolution. Other limitation is with background traffic. The authors say that it is obtained from a university router, but no more details about topology or services are provided.

3.2.5. UNSW-NB15 (2015)

The above mentioned datasets cannot meet current research requirements due to dynamically changing security and operational demands of a network. Despite of having dataset intrinsic weaknesses, they do not
Table 2: Dataset statistics presents the total number of flows, simulation periods, 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.

| Statistical features | 16 hours | 15 hours |
|----------------------|----------|----------|
| No. of flows         | 987,627  | 976,882  |
| Source bytes         | 4,860,168,866 | 5,940,523,728 |
| Destination bytes    | 44,743,560,943 | 44,303,195,509 |
| Source packets       | 41,168,425 | 41,129,810 |
| Destination packets  | 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               |          |          |
| Source IP            | 40       | 41       |
| Destination IP       | 40       | 45       |

have modern day normal traffic nor they have updated attack patterns. UNSW-NB15 dataset is recently proposed by Moustafa et al. [49] to address these issues. It is a hybrid dataset which consists of real modern normal network activities coupled with synthetic updated attacks. This is the main motivation to use UNSW-NB15 dataset for our research.

UNSW-NB15 dataset is generated with the help of attack generation tool called IXIA PerfectStorm. It contain nine families of real and updated attacks against several servers. Authors’ collected tcpdump traces of the network traffic, for a total duration of 31 hours at the beginning of 2015. From these network logs, they generated a dataset consists of 49 features for every network flow. A complete detail about dataset creation process, architectural framework, feature extraction phases and dataset’s issues will be presented in the next Section 4.

4. Anatomy of UNSW-NB15 Dataset

Section 3.2.5 discusses the motivation and reasons behind the use of UNSW-NB15 dataset for our research. In this section we will discuss:

1. UNSW-NB15 dataset creation process
2. Architectural framework
3. Feature extraction process
4. Dataset distribution and Issues

4.1. UNSW-NB15 Dataset Creation Process

This dataset is generated with the help IXIA [50] traffic generator tool which is configured with three virtual servers. First and third server were configured to generate normal network traffic while Server 2 was build to generate abnormal or malicious attack traffic. Considering network performance and exploitation methodology, IXIA is configured to generate one attack per second in phase 1. However, in the second phase of the simulation, IXIA is configured to launch ten attacks per seconds. In total, testbed generated 100 GB of trace data in two episodes of 16 and 15 hours each. Table 2 presents statistical summary of both phases of the simulation.
4.2. Architectural Framework

Figure 1 elaborates the complete model developed to create UNSW-NB15 dataset. The process starts from traffic capturing phase which is achieved with help of tcpdump utility. The captured traffic is stored in pcap files which are then feed into Argus [51] and Bro-IDS [52] for features extraction. Once features are extracted, the output is compared with total number of flows for any discrepancy.

4.3. Feature Extraction Phases

In UNSW-NB15 dataset creation process, features extraction is performed with the help of Argus [51], Bro-IDS [52] and custom utilities [49]. The pcap files are feed into Argus and Bro-IDS. Argus has the capability to process raw network traffic. It works on client-server model, where Argus-server transforms raw pcaps files into Argus compatible format. Argus-client then able to read and extract features from Argus files.

Bro-IDS is an open-source network traffic analyzer and anomaly detector. It is predominantly a security monitor that inspect all network traffic against malicious activities. The Bro-IDS tool is configured to generate three log files (i) conn file which records all connection information seen on the pcap files (ii) http file which includes all HTTP requests and replies and (iii) ftp file which records all activities of the FTP protocol.

The output of Argus and Bro-IDS is feed into MS-SQL server database for cross-matching of features and in order to extract more features by using flow features as represented in Table 3. The ‘Type’ field in Tables 3, 4, 6, 5, 7 and 8 represents the datatype of the attribute. Type field includes N: nominal, I: integer, F: float, T: timestamp and B: binary types. All these tables represent features of UNSW-NB15 dataset, these tables are split into multiple tables for better readability based on their family.

4.4. Matched Features of Argus & Bro-IDS Tools

These features include a variety of packet and flow based features. These features are generated by cross matching of features generated by Argus and Bro-IDS tool. Flow based features require low computational overhead as compared to packet based features which perform DPI because they only analyze connected packets of the network traffic. Furthermore flow based features are based on direction, inter-arrival time and inter-packet length [53]. The matched features are categorized into three groups (i) Basic, (ii) Content, and (iii) Time which are described in Tables 4, 5 and 6 respectively.
Table 3: **Flow based features** require low computational overhead as compared to packet based features which perform DPI because they only analyze connected packets of the network traffic. Furthermore flow based features are based on a direction, an inter-arrival time and an inter-packet length [53].

| #  | Name | Type | Description                        |
|----|------|------|------------------------------------|
| 1  | srcip| N    | Source IP address                 |
| 2  | sport| I    | Source port number                |
| 3  | dstip| N    | Destination IP address            |
| 4  | dsport| I   | Destination port number           |
| 5  | proto| N    | Transaction protocol              |

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

Table 5: **Content Based Features**

| #  | Name   | Type | Description                                                |
|----|--------|------|------------------------------------------------------------|
| 19 | swin   | I    | Source TCP window advertisement                           |
| 20 | dwin   | I    | Destination TCP window advertisement                      |
| 21 | stcpb  | I    | Source TCP sequence number                                |
| 22 | dtcpb  | I    | Destination TCP sequence number                           |
| 23 | smeansz| I    | Mean of the flow packet size transmitted by the src        |
| 24 | dmeansz| I   | Mean of the flow packet size transmitted by the dst        |
| 25 | trans_depth| I | the depth into the connection of http request/response transaction |
| 26 | res_bdy_len| I | The content size of the data transferred from the servers http service |
Table 6: Time based Features

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

4.5. Additional features from the matched features

Authors [49] generated additional twelve features from the matched features are depicted in Table 7. This table 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 defense point of view, whereas connection features are solely created to provide defense during attempt to connection scenarios.

4.6. Labelled Features

Dataset labeling is performed with the help of report generated by IXIA tool. This report 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). The data set is labelled according to Table 8.

4.7. Data Set Records Distribution and Issues

UNSW-NB15 dataset contains more than 2.5 million records if we apply ML on the whole dataset it will demand a lot of computational resources which will not be feasible. However, Authors [49] has provided a partition of dataset which can be used for machine learning. Distribution of different attack categories and normal traffic is presented in Figure 2. From this figure we can analyze that dataset is highly imbalanced that will effect classification accuracy as discussed in Section 5.3. 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.

1. Fuzzers
2. Analysis
3. Backdoors
4. DoS
5. Exploits
6. Generic
7. Reconnaissance
8. Shellcodes
9. Worms

* Explanation of these attacks is out of scope of this article.
Table 7: Additional Generated Features

| #   | Name              | Type | Description                                                                                                                                 |
|-----|-------------------|------|--------------------------------------------------------------------------------------------------------------------------------------------|
| 36  | is_sm_ips_ports   | 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  | ct_state_ttl      | I    | No. for each state (6) according to specific range of values for source/destination time to live (10) (11).                                |
| 38  | ct_flw_http_mthd  | I    | No. of flows that has methods such as Get and Post in http service                                                                         |
| 39  | is_ftp_login      | B    | If the ftp session is accessed by user and password then 1 else 0.                                                                           |
| 40  | ct_ftp_cmd        | I    | No of flows that has a command in ftp session.                                                                                               |
|     |                   |      | **Connection features**                                                                                                                      |
| 41  | ct_srv_src        | I    | No. of connections that contain the same service (14) and source address (1) in 100 connections according to the last time (26).          |
| 42  | ct_srv_dst        | I    | No. of connections that contain the same service (14) and destination address (3) in 100 connections according to the last time (26).  |
| 43  | ct_dst_ltm        | I    | No. of connections of the same destination address (3) in 100 connections according to the last time (26).                                   |
| 44  | ct_src_ltm        | I    | No. of connections of the same source address (1) in 100 connections according to the last time (26).                                        |
| 45  | ct_src_dport_ltm  | 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  | ct_dst_sport_ltm  | 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  | ct_dst_src_ltm    | I    | No of connections of the same source (1) and the destination (3) address in in 100 connections according to the last time (26).        |

Table 8: Labelled Features

| #   | Name | Type | Description                                                                                                                                 |
|-----|------|------|--------------------------------------------------------------------------------------------------------------------------------------------|
| 48  | attack_cat | 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  | Label | B    | 0 for normal and 1 for attack records                                                                                                       |
5. Machine Learning Experiments and Results

In this section we will present the machine learning experiments performed and their findings. Machine learning can be classified into different types e.g. (i) Supervised, (ii) Unsupervised (iii) Reinforcement Learning. In supervised machine learning, training data along with label is provided to the algorithm to create a model. Training data consists of input vector (known as features) and output (class label). Once model is constructed, the performance of the model is evaluated on test data. Supervised machine learning process is shown in Figure 3.

5.1. Algorithm Selection

Machine learning algorithms are classified into different families based on how they operate. Parametric, non-parametric, probability based, tree based, neural networks based etc. are most commonly employed algorithms. In this research, we choose algorithms from diverse categories. We include following algorithms in our experiments.

1. Naive Bayes Classifier (NB) - Probabilistic
2. K-Nearest Neighbor (kNN) - Non-parametric
3. Random Forest (RF) - Tree based classifier
4. Multi-layer Perceptron (MLP) - Motivated by human brain operation

5.1.1. Naive Bayes Classifier (NB)

Naive Bayes classifier is a probabilistic classifier that works on the principle of conditional probability. Conditional probability says that what is the probability of occurring an event given that a certain event has already occurred. After calculating the conditional probability of an event it applies Bayes theorem to predict the correct class of the instance. Conditional probability and Bayes theorem can be calculated as per Equation 1 and 2 respectively.

\[
P(A|C) = \frac{P(A,C)}{P(C)} (1)
\]

\[
P(C|A) = \frac{P(A|C)P(C)}{P(A)} (2)
\]
5.1.2. **K-Nearest Neighbor (KNN)**

K Nearest Neighbor (KNN) is one of the most simplest nonparametric technique to classify samples [54]. It computes the nearest distances of a query $x_q$ from the given points in the sample space. For classification problems, $NN(k, x_q)$, it assigns the unlabeled point to the class of its $k$ nearest neighbors by plurality voting. To avoid ties, $k$ is always chosen to be an odd number.

Number of different techniques have been proposed in literature [55] to calculate nearest distance of a neighbor such as, City block distance (Manhattan distance), Euclidean distance, Chebyshev distance, Hamming distance etc. Usually distance are measured with Minkowski distance or $L^p$ norm, which is defined in Eq. 3

$$L^p(x_j, x_q) = (\sum |x_{j,i} - x_{q,i}|^p)^{1/p}$$  \hspace{1cm} (3)

where,

- $x_q$: query point,
- $x_j$: example point,
- if $p = 1$ it is Manhattan distance,
- if $p = 2$ it will be Euclidean distance

Different ‘$k$’ values will result in different outputs. Higher $k$ values will lead to overfitting issues and lower will cause underfitting problem. Thus an optimal value of $k$ should be considered. We configured $k=3$ in our simulation.

5.1.3. **Random Forest (RF)**

Random Forest is basically a tree based classifier that builds a set of decision trees randomly. The classification of an input sample is determined by the majority classification by the ensemble. It utilizes different ensemble techniques [56] that is why it is also categorized as ensemble classifier. It can perform classification and regression tasks. The performance of RF classifier is generally better than decision trees on unseen data [57].
5.1.4. Multi-Layer Perceptron (MLP)

Multilayer perceptron is a feed forward Artificial Neural Network (ANN) inspired from human Neural Network (NN) [58]. A typical MLP consists of input, output and a number of hidden layers or computational units [59]. Inputs are fed to input layer in the form of feature vector. Input is processed by the hidden layers and the purpose of output layer is to generate the output i.e. the label in this case. At hidden layer there is a learning algorithm that adjusts the synaptic weights associated with each neuron to reduce the error [60] and the activation function. The activation function simply applies a threshold and squishes the response very similar to as biological neurons. Number of activation functions have been proposed in the literature as in [61]. The choice of the activation function depends upon the nature of the problem and system designer. Figures 4 shows the schematic representation of a neuron. Mathematically, MLP can be defined as:

$$y(x) = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

where, $x_i$ and $w_i$ are inputs and weights respectively. $b$ is bias and $f$ is the activation function.

5.2. Evaluation Criteria

In literature different methods are proposed to measure the accuracy of a classifier (i) Separate Training and Test Sets (ii) $k$-fold Cross-validation (iii) $N$-fold Cross-validation (iv) Leave One Out [62]. We will use $k$ fold Cross-Validation (CV) technique because it tries to reduce overfitting. Overfitting is a serious problem in ML in which model tries to predict a trend that is too noisy.

Problem with different values of $k$ for each classifier.

$k$-Fold Cross-Validation Technique:

In $k$ fold cross validation approach dataset of 'N' number of samples is divided into $k$ equal parts known as folds. If $N$ is not exactly divisible by $k$, the final part will have fewer instances than the other $k-1$ parts. $k$ rounds of training and testing are performed. In each round $k-1$ folds are used for training and a different fold for testing or validation [63] is used. After the completion of all rounds the overall predictive accuracy and standard error is calculated as per the Equation 5 and 6 respectively.

$$Average\ Accuracy = \frac{1}{N} \sum_{i=1}^{k} (Correctly\ Classified\ Instances)$$
### Table 9: k folds Cross-validation summary

| Classifier | Accuracy (in percentage) |
|------------|--------------------------|
|            | 10 | 8  | 6  | 4  | 2  |
| KNN        | 76.56 | 76.02 | 75.50 | 75.00 | 74.49 |
| NB         | 52.90 | 52.43 | 51.67 | 51.19 | 50.59 |
| RF         | 82.14 | 81.64 | 81.34 | 80.92 | 80.31 |
| MLP        | 69.56 | 69.06 | 68.58 | 68.08 | 67.61 |

Table 9: k folds Cross-validation summary

\[
\text{Standard Error} = \sqrt{p(1-p)/N} \tag{6}
\]

where, \(p\) is the average predictive accuracy calculated by using Eq. 5

#### 5.3. Results

As discussed in Section 5.2 we used \(k\)-fold cross validation technique to measure classifiers’ accuracy. We tried different values of \(k\) (10, 8, 6, 4, 2) to further reduce the variance. Variance is an error from sensitivity to small fluctuations in the training set [64]. Table 9 portrays average accuracy of classifiers for all folds. We observed that there is a marginal difference in the accuracy with different values of \(k\) in k-folds rounds which shows that dataset is well distributed even for \(k=2\) worse case classifier performed well. The average accuracy of all classifiers for all folds is 75.51%, 51.76%, 81.27% and 68.58% for k Nearest Neighbor, Naive Based, Random Forest and Multi Layer Perceptron respectively. Classifiers average accuracy is calculated by taking arithmetic mean of classifiers’ accuracy over all folds.

![Accuracy Vs Sample Size](image)

Figure 5: Attack Detection vs Traffic Type and Sample Size
Attack detection trend with respect to sample size for different types of attacks is presented in the Figure 5. It shows classifier detection accuracy with respect to different types of attacks and corresponding class instances. Few notable observations from this graph are presented below.

1. Attack detection rate is directly proportional to the sample size of the respective traffic or attack category. It means that traffic category having large number of samples are more likely to be correctly classified and vice-versa.
2. Detection rate can be improved further if we increase number of samples for that traffic or have more balanced dataset.
3. Since NB classifier works on the principle of conditional probabilities see Section 5.1.1, it almost failed to detect DoS and Reconnaissance attacks despite of having reasonable sample size. Because in DoS and Reconnaissance, every packet or hacking attempt or flow is autonomous and independent of the previous one having no causal relationship or dependency.
4. Similarly NB accuracy for detecting backdoors and shellcodes traffic is relatively better than other classifiers, because hackers perform a series of attacks to exploit backdoor or shellcode in a system, that possibly gave rise to the causal relation between different events and thus the accuracy.

Figure 6 presents the confusion matrix for all four classifiers used in our study. In machine learning, Confusion Matrix (CM) is used to visually analyzed classifier behavior in predicting classes and confusion across classes. Each row of the matrix represents the instances in a predicted class while each column represents the instances in an actual class (or vice versa). CM is a diagonal matrix in ideal case. Few notable observations from the confusion matrices are presented below.

1. All classifiers confused between worms and exploits. Worm is a type of malware that spreads itself from one computer to another without any human interaction [65]. An exploit is a piece of software, or a sequence of commands that takes advantage of a bug or vulnerability present in a software or hardware system [66].
2. NB also misclassified worm as shellcode, shellcode is a payload of an exploit. So few possible causes of misclassification may be (i) Worm has small sample size (ii) Overlapping features set. So in order to address this issue we should increase its sample size or we need to extract more distinguished features from the actual dataset.
3. Analysis is the second most misclassified attack after worms. It contains port scanning, spam messages and html files penetrations [49]. One obvious reason of misclassification is low samples size as compared to other classes see Figure 5
4. Similarly all classifiers become confused to detect backdoors correctly. However NB detection rate is relatively better than other classifiers because of its working methodology as discussed above.

The amount of traffic an IDS needs to monitor is very large even for a small size home network. Traffic analysis and attack detection becomes more exhaustive, time consuming and computationally expensive process. The job becomes more difficult when network size grows. Redundant and irrelevant features also impacts classifier’s performance [67]. In the next section we will discuss how redundant and irrelevant features can be removed from the dataset while maintaining and even improving the performance of the classifier.

6. Feature Selection (FS)

Feature selection is an important step which is performed to select important features. The objective of feature selection is to reduce the effect of “curse of dimensionality” by removing redundant or irrelevant features without compromising on classifier accuracy [68].

Feature selection is NP-hard problem [69]. Finding a subset of optimal features is a difficult tasks. A major challenge is to choose appropriate feature-selection methods that can precisely determine the relevance of features to the intrusion detection task and the redundancy between features.
6.1. Feature Selection Methods

Researchers have proposed three different approaches for feature selection [70] (i) Filter (ii) Wrapper (iii) Embedded.

6.1.1. Filter Method

Filter based feature selection algorithms are totally independent from any predictor function [71]. It is based on feature ranking algorithms, that make use of an evaluation criterion and a limit or threshold to calculate the feature relevance and decide whether to keep that feature or discard it. The feature relevance is determined by its capability to provide useful information about the different classes [67]. Filter algorithms are usually computationally less expensive than the other methods [68]. Pearsons Correlation, Linear Discriminant Analysis (LDA), Chi-Square method etc. are few examples of filter based feature selection technique.


6.1.2. Wrapper Method

Wrapper based feature selection methods has three components: a search strategy, a predictor, and an evaluation function [70].

- The search strategy determines the subset of features to be evaluated.
- The predictor can be any classification method.
- Classifier (predictor) performance is used as the evaluation function to assess the subset of features defined by the search strategy so as to find the optimum subset that gives the best accuracy of it.

The performance in terms of selection of strong features of wrapper methods is better than filter based techniques, however they are more time consuming and require more computational resources [72]. Sequential search and Heuristic based search algorithms are two main categories of wrapper based feature selection.

6.1.3. Embedded Method

Wrapper based techniques are more time consuming. Embedded methods incorporate an interaction between feature selection and learning process. They make better use of the available data and avoid retraining the predictor for every selected feature subset [73]. There are various embedded feature selection techniques have been proposed in the literature such as Micro-Genetic Algorithm (GA), Embedded Particle Swarm Optimization (PSO), etc. [74].

6.2. Studied Feature Selection Methods

Generally entropy or correlation based techniques are commonly employed for feature selection/weighting. Thus in this study we also examined gain ratio, chi-square method and pearson correlation method for feature selection. However in addition to these three approaches we also studied metaheuristic - combinatorial optimization based approach i.e. tabu search. The reason for including this approach in our study is that it has shown improved results over entropy and correlation based methods [75]. All four approaches we used in our research are presented below.

1. Gain Ratio
2. Chi-Square Method
3. Pearson Correlation Method
4. Tabu Search

6.2.1. Gain Ratio

Gain Ratio is a derive version of Information Gain (IG). IG is an entropy based feature selection method that measures the importance or relevance of a feature with respect to the corresponding class. Entropy can be defined as a measure of unpredictability or uncertainty irrespective of the origin [76] and can be calculated by using Eq. 7

\[ H(S) = - \sum_{i=1}^{c} p_i \log_2 p_i \]  

where,
S = training dataset,
C = No. of target classes,
\( p_i \) = proportion of examples in \( S \) belonging to target class \( i \)
Gain Ratio depends upon the Information Gain of that feature. Information Gain can be calculated by using Eq. 8. Gain Ratio is the ratio of IG to Intrinsic Value (IV).

\[
Gain(S, A) = H(S) - \sum_{v \in A} \frac{|S_v|}{|S|} H(S_v)
\]

where,

S = training set,

6.2.2. Chi-Square Feature Method

Chi-Square is feature selection method based on $\chi^2$ test. It calculates the independence of two events A and B if $P(AB) = P(A)P(B)$ or $P(A|B) = P(A)$ and $P(B|A) = P(B)$. In feature selection, we actually want to calculate whether output variable (class) is dependent on input variable (feature) or not. If it is independent, then the input variable is a candidate feature that may be irrelevant and can be removed. Mathematically, Chi-Square test can be expressed as Eq. 9,

\[
\chi^2 = \sum_{i=1}^{n} \frac{(E_i - O_i)^2}{E_i}
\]

where,

$E_i$ is the expected value of feature,

$O_i$ is the observed value of feature,

6.2.3. Pearson Correlation Method

Pearson correlation is a filter based feature selection approach used to measure linear relationship or dependency between two variables. It is used to find the association between continuous features and the class attribute. It is also used to find feature-feature correlation to remove redundant features.

6.2.4. Tabu Search

Tabu Search (TS) was first introduced by Fred Glover [21, 22] as a general iterative metaheuristic for solving combinatorial optimization problems. It is a form of local neighborhood search. Each solution $S \in \Omega$ has an associated set of neighbors $N(S) \subseteq \Omega$, where $\Omega$ is a set of feasible solutions. A solution $S' \in N(S)$ can be reached from $S$ by an operation called a move to $S'$. TS moves from a solution to its best admissible neighbor, even if this causes the objective function to deteriorate. To avoid cycling, solutions that were recently explored are declared forbidden or tabu for a number of iterations. The tabu status of a solution is overridden when certain criteria (aspiration criteria) are satisfied. Sometimes intensification and diversification strategies are used to improve the search. In the first case, the search is accentuated in promising regions of the feasible domain. In the second case, an attempt is made to consider solutions in a broad area of the search space. TS algorithm parameters are mentioned in Table 10.

We used wrapper based approach to calculate the fitness of each solution generated randomly in TS. We used Random Forest (RF) Classifier as a predictor in TS-wrapper. RF is discussed in section 5.1.3. Fitness of each solution is calculated based on Eq. 10. We run the simulation for 100 iterations and found the optimal solution having 17 features (including class label also) at 76th iteration.

\[
Cost = \alpha \ast e + (1 - \alpha) \ast n
\]

where,

$\alpha$ is a user-defined parameters between $[0, 1]$. We set $\alpha$ to 0.5,

$e$ is RF error,

$n$ is number of features included in the candidate solution.
Table 10: Tabu Search algorithm parameters

| Parameter          | Value |
|--------------------|-------|
| Tabu List Size     | 7     |
| No. of neighbor    | 6     |
| Aspiration Level   | 0.05  |
| No. of Iterations  | 100   |

Gain Ratio and Pearson Correlation based methods calculate the importance of each feature in terms of "Rank or weight" ranging between [0, 1]. For Chi Square method we normalized the output between [0, 1]. Table 11 present attributes and their corresponding weights for all three filter based feature selection technique and TS. Tabu Search column consists of binary value '0' or '1', zero means the attribute is not present in the final optimal feature set and has been removed.

6.3. Results After Feature Selection

We apply a threshold (a cut-off) on the attributes’ weights for all filter based techniques. Initially we selected all those features whose weights are greater than or equal to 0.2 (cut-off). Then we apply a cut-off at 0.15. Figure 7 and 8 presents classifier accuracy against number of features and Table 13 and 14 presents classifier computational complexity for thresholds 0.2 and 0.15 respectively.

Tabu Search gives us better results and reduces number of features up to 62%. We observe 1 - 2% increase for RF, upto 4% increase for KNN and a significant increase for MLP which is upto 7%. We also observe that there is a slight decrease in the accuracy for NB. The time complexity for TS is also significantly reduced. Time complexity for MLP is exceptionally reduced by 95% while for RF, NB and KNN classifiers it is reduced up to 40%, 45% and 20% respectively.

We also compared the results obtained from TS-RF with GA-LR proposed by [77]. Table 12 shows that TS-RF achieved higher accuracy at lower number features compared to GA-LR wrapper method.

7. Conclusion & Future Work

Signature-based IDS can only detect attacks whose signatures are developed and incorporated in the signature database while anomaly-based systems can detect unknown attacks. However they require ample amount of training time after deploying in production network which is usually not a possible option. In addition to that their false positive rate is very high. In this research we studied potential application of machine learning to detect network-based unknown attacks. Our study focused on UNSW-NB15 dataset because it consists of hybrid real modern normal network traffic with synthetic updated attacks. Initially, we applied machine learning on the original dataset without applying any feature selection technique, the key findings are summarized below.

1. We achieved good classification accuracy for RF and KNN algorithms while acceptable and average results for MLP and NB are achieved respectively.
2. Classifier detection accuracy declined for attacks category having low number of instances in the dataset. It can be improved if it has more number of samples for that traffic type or well balanced dataset.
3. Confusion matrices show that classifiers misclassified worms and analysis traffic to exploits category. One common possible reason is the low sample size of analysis and worm traffic.

In the second phase of our research we proposed a new wrapper-based Tabu Search - Random Forest (TS-RF) feature selection algorithm for IDS dataset. TS-RF wrapper exploits Tabu search metaheuristic algorithm for feature search / feature weighting and Random forest as a learning algorithm. The selection of optimal feature set is determined by maximizing classification accuracy and minimizing number of features. The optimal features generated from TS-RF are compared with three filter-based feature selection techniques
Figure 7: Classifier Accuracy vs No. of Features (Cutoff 0.2)

Figure 8: Classifier Accuracy vs No. of Features at (Cutoff 0.15)
Table 11: Results of Feature Selection Methods

| Feature          | Pearson Correlation Method | Gain Ratio Method | Chi Square Method | Tabu Search |
|------------------|-----------------------------|-------------------|-------------------|-------------|
| ct_dst_sport_ltm | 0.395                       | 0.377             | 0.320             | 1           |
| ct_dst_src_ltm   | 0.363                       | 0.175             | 0.305             | 1           |
| ct_src_dport_ltm | 0.363                       | 0.262             | 0.286             | 1           |
| sttl             | 0.36                        | 0.505             | 0.282             | 1           |
| ct_srv_dst       | 0.35                        | 0.19              | 0.327             | 1           |
| ct_srv_src       | 0.348                       | 0.172             | 0.306             | 1           |
| ct_dst_ltm       | 0.337                       | 0.195             | 0.288             | 1           |
| xServ            | 0.24                        | 0.38              | 0.291             | 1           |
| is_sm_ips_ports  | 0.096                       | 0.225             | 0.005             | 1           |
| smeans           | 0.095                       | 0.25              | 0.745             | 1           |
| dloss            | 0.054                       | 0.188             | 0.219             | 1           |
| ct_flw_http_mthd | 0.051                       | 0.121             | 0.038             | 1           |
| dbytes           | 0.043                       | 0.219             | 0.491             | 1           |
| sbytes           | 0.024                       | 0.272             | 1                 | 1           |
| sloss            | 0.022                       | 0.18              | 0.178             | 1           |
| response_body_len| 0.014                       | 0.182             | 0.082             | 1           |
| ct_src_ltm       | 0.312                       | 0.153             | 0.243             | 0           |
| ct_state_ttl     | 0.306                       | 0.432             | 0.288             | 0           |
| xState           | 0.284                       | 0.328             | 0.165             | 0           |
| swin             | 0.268                       | 0.278             | 0.093             | 0           |
| dwin             | 0.263                       | 0.271             | 0.099             | 0           |
| xProt            | 0.245                       | 0.291             | 0.283             | 0           |
| rate             | 0.225                       | 0.17              | 0.302             | 0           |
| dttl             | 0.214                       | 0.456             | 0.283             | 0           |
| dtcpb            | 0.208                       | 0.271             | 0.090             | 0           |
| stcpb            | 0.208                       | 0.271             | 0.090             | 0           |
| dmean            | 0.207                       | 0.2               | 0.364             | 0           |
| dload            | 0.203                       | 0.205             | 0.276             | 0           |
| ackdat           | 0.164                       | 0.254             | 0.216             | 0           |
| tcprtt            | 0.161                       | 0.259             | 0.224             | 0           |
| synack            | 0.141                       | 0.251             | 0.225             | 0           |
| sload            | 0.098                       | 0.22              | 0.672             | 0           |
| smpkt             | 0.092                       | 0.132             | 0.245             | 0           |
| dpkt              | 0.067                       | 0.207             | 0.291             | 0           |
| dur              | 0.062                       | 0.156             | 0.293             | 0           |
| djit              | 0.052                       | 0.174             | 0.206             | 0           |
| ct_ftp_cmd        | 0.047                       | 0.123             | 0                 | 0           |
| is_ftp_login      | 0.047                       | 0.123             | 0                 | 0           |
| spkts             | 0.045                       | 0.168             | 0.228             | 0           |
| trans_depth       | 0.041                       | 0.117             | 0.018             | 0           |
| sjit              | 0.033                       | 0.168             | 0.215             | 0           |
| dinpkt            | 0.03                        | 0.219             | 0.270             | 0           |

i.e. Gain Ratio, Chi-Square, Pearson Correlation and one wrapper-based method i.e GA-LR. Experiments show promising results for TS-RF method. Key findings of the simulation are summarized below.

1. TS-RF reduces the number of features by 62% while improving classification accuracy sufficiently.
2. Since TS-RF has reduced the number of features due to which the time complexity is also reduced
Table 12: Comparison of TS-RF with GA-LR Wrapper Method Results show that TS-RF achieved higher accuracy at reduced no. of features

| Feature Selection Method | No. of Features | Classifier       | Accuracy |
|--------------------------|-----------------|------------------|----------|
| GA-LR                    | 20              | Decision Tree    | 81.72    |
| TS-RF                    | 16              | Decision Tree    | 83.59    |

Table 13: Shows the impact of feature selection techniques on time complexity of classifiers at Cutoff=0.2, +ve and -ve values show percentage improvement and decrement respectively

| Feature Selection Method | RF (%) | NB (%) | KNN (%) | MLP (%) |
|--------------------------|--------|--------|---------|---------|
| Chi-Square               | +11.512| +25.76 | No improvement | +0.90   |
| Gain Ratio               | +33.30 | +46.01 | -60     | +8.02   |
| Pearson Correlation      | +37.47 | +57.67 | -40     | -67.55  |
| Tabu Search              | +39.44 | +45.40 | +20     | +95.40  |

Table 14: Impact of feature selection techniques on time complexity of classifiers at Cutoff=0.15, +ve and -ve values show percentage improvement and decrement respectively

| Feature Selection Method | RF (%) | NB (%) | KNN (%) | MLP (%) |
|--------------------------|--------|--------|---------|---------|
| Chi-Square               | +9.42  | +26.38 | +40     | -87.70  |
| Gain Ratio               | +6.88  | +12.88 | +40     | -2.24   |
| Pearson Correlation      | +27.37 | +44.17 | +60     | +4.44   |
| Tabu Search              | +39.44 | +45.40 | +20     | +95.40  |

3. TS-RF achieved better accuracy at less number of features as compared to GA-LR.

In future we plan to address class imbalance problem present in UNSW-NB15 dataset because it does not only impact the classifier accuracy but also it increases misclassification rate and false positives. Extraction of new discriminant / salient features from the original data by applying deep learning may also help to reduce misclassification rate and improve accuracy. Another possible avenue is to work on the application of metaheuristic algorithms like TS or other evolutionary computing or nature inspired algorithm for threat detection and feature selection because these optimization algorithms have also shown better results in other domains.

References

[1] H. Venter, J. H. Eloff, A taxonomy for information security technologies, Computers & Security 22 (4) (2003) 299–307.
[2] Cyberattack: cyberattack: computer attack, exploitation, apt, https://en.wikipedia.org/wiki/Cyberattack/, accessed: 2018-12-18.
[3] Symantec, Internet security threat report (vol. 23), Tech. rep., Symantec Corporaton (2018).
[4] J. M. Ehrenfeld, Wannacry, cybersecurity and health information technology: A time to act, Journal of medical systems 41 (7) (2017) 104.
[5] G. Welchman, The hut six story: breaking the enigma codes, McGraw-Hill Companies, 1982.
[6] P. Taylor, Hackers: Crime and the digital sublime, Routledge, 2012.
[7] B. Brewster, B. Kemp, S. Galeh bkhtiai, B. Akhgar, Cybercrime: attack motivations and implications for big data and national security, in: Application of Big Data for National Security, Elsevier, 2015, pp. 108–127.
[8] A. Bessi, E. Ferrara, Social bots distort the 2016 us presidential election online discussion (2016).
[9] P. N. Howard, B. Kollanyi, S. Woolley, Bots and automation over twitter during the us election, Computational Propaganda Project: Working Paper Series (2016).
[10] H. Allcott, M. Gentzkow, Social media and fake news in the 2016 election, Journal of Economic Perspectives 31 (2) (2017) 211–36.
