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"IMPLEMENTATION AND EVALUATION OF NETWORK ANOMALY DETECTION ALGORITHMS"

Submitted in the partial fulfillment for the requirements of the degree of

BACHELOR OF ENGINEERING

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COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the Project work entitled **"IMPLEMENTATION AND EVALUATION OF NETWORK ANOMALY DETECTION ALGORITHMS"** is a bonafide work carried out by **Mr. MAHIDHAR C (1BY10CS037), Mr. NITESH A JAIN (1BY10CS047), Ms. PADMAVATHI K (1BY10CS048), Mr. PARTHASARATHY M ALWAR (1BY10CS049)** in partial fulfillment for the award of **Bachelor of Engineering Degree in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum during the year 2013-14. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in this report. The project report has been approved as it satisfies the academic requirements in respect of project work for the B.E degree.

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ABSTRACT

Anomaly detection refers to the problem of finding patterns in data that do not conform to expected behavior. These non-conforming patterns are often referred to as anomalies or outliers. Intrusion detection in computer networks is the process of monitoring for and identifying attempted unauthorized system access or manipulation. This project examines the application of Statistical Modeling for detecting intrusions in computer networks.

Currently, a rule based Network Intrusion Detection System (NIDS) relies on the details of previously known attacks. By knowing the attack vector, rules can be implemented in the firewall and/or other defense tools to recognize the attack and appropriately counter it. However the main drawbacks of this system are - New unknown attacks cannot be countered effectively till encountered and Damage to the system rendering any future counters to the attack useless.

We propose a small lightweight NIDS, which is a method to detect and identify attacks in real time. It will concentrate on a limited category of attacks from standard datasets containing well established and tested attack vectors, with considerations to latency. The network will be modeled by the NIDS using machine learning algorithms based on Naive Bayes Models.

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CHAPTER 1

INTRODUCTION

Chapter 1

INTRODUCTION

Computer networks are telecommunication networks which allow computers to exchange data. Network security is implemented on a variety of computer networks to secure daily transactions and communications among businesses, governments and individuals.

1.1 Overview

The current network security technologies (such as Firewall, IDS/ IPS) do provide security to networks but have limitations in terms of detecting only the known attack patterns. The system becomes prone to unknown vulnerabilities until the signatures of such attacks are found and configured in the signature databases of network security solutions. The moment attack pattern changes, the signature based solutions fail.

1.2 Network Security

Network security[1] consists of the provisions and policies adopted by a network administrator to prevent and monitor unauthorized access, misuse, modification, or denial of a computer network and network-accessible resources. Network security involves the authorization of access to data in a network, which is controlled by the network administrator.

1.2.1 Anomaly in Network Security

In network security, **anomaly** (or **outlier**) is an item, event or observation which does not conform to an expected pattern or other items in a dataset. Typically the anomalous items will translate to some kind of problem such as an attack on the network or a network defect. Anomalies are also referred to as outliers, novelties, noise, deviations and exceptions.

1.2.2 Intrusion Detection Systems

An Intrusion Detection System (IDS)[2] is a device or software application that monitors network or system activities for malicious activities or policy violations and produces reports to a management station as illustrated in figure 1.1. Intrusion detection and prevention systems (IDPS) are primarily focused on identifying possible incidents, logging

information about them, and reporting attempts.

In a passive system, the intrusion detection system (IDS) sensor detects a potential security breach, logs the information and signals an alert on the console and/or owner. In a reactive system, also known as an intrusion prevention system (IPS), the IPS auto-responds to the suspicious activity by resetting the connection or by reprogramming the firewall to block network traffic from the suspected malicious source. The term IDPS is commonly used where this can happen automatically or at the command of an operator; systems that both "detect (alert)"and "prevent".

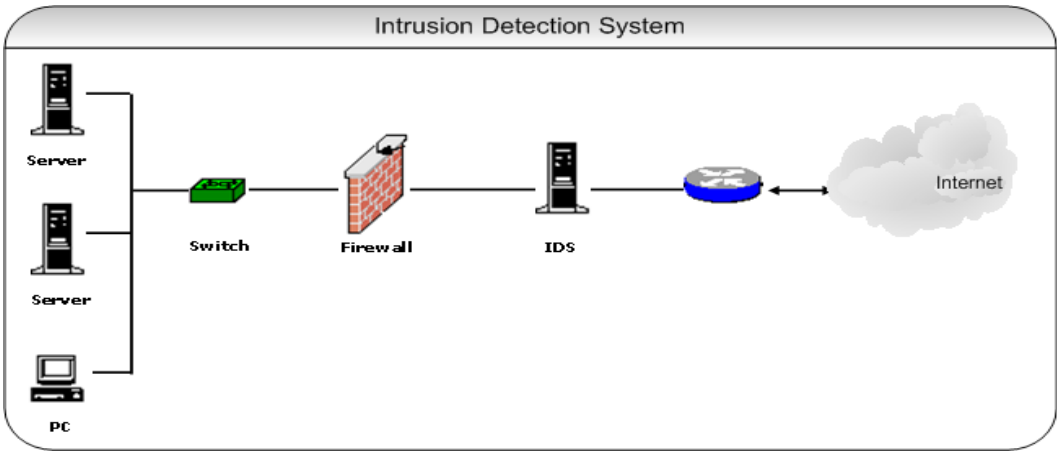


Figure 1.1 Intrusion Detection Systems

1.2.3 Attack Classification

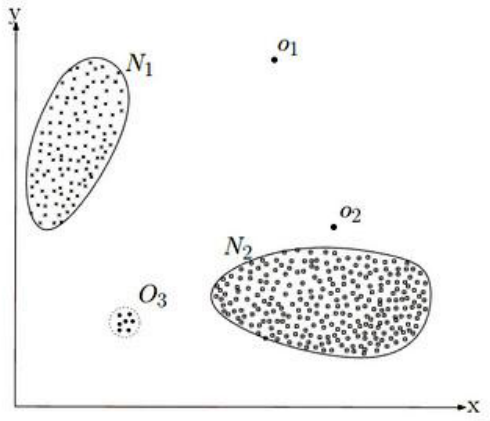
In computer networks, an attack is any attempt to destroy, expose, alter, disable, steal or gain unauthorized access to or make unauthorized use of an asset.[3] Common attack classes and their types are outlined in table 1.1.

Attack Class	Attack Type
Probe	portsweep, ipsweep, quesosatan, msscan, ntinfoscan, lsdomain, illegal-sniffer.
DoS	apache2, smurf, neptune, tosnuke, land, pod, back, teardrop, tcpreset, syslogd, crashiis, arppoison, mailbomb, selfping, processtable, udpstorm, warezclient.
R2L	dict, netcat, sendmail, imap, ncftp, xlock, xsnoop, sshtrojan, framespoof, ppmacro, guest, netbus, snmpget, ftpwrite, hhtptunnel, phf, named.
U2R	sechole, xterm, eject, ps, nukepw, secret, perl, yaga, fdformat, ffbconfig, casesen, ntfsdos, ppmacro, loadmodule, sqlattack.

Table 1.1 Attacks present in DARPA 1999 Dataset

1.3 Machine Learning and its Applications

Machine learning, a branch of artificial intelligence, concerns the construction and study of systems that can learn from data. For example, a machine learning system could be trained on network traffic to learn to distinguish between anomalous and normal traffic. After learning, it can used to classify the incoming traffic into anomalous and normal traffic as shown in figure 1.2.



A simple example of anomalies in a 2-dimensional data set.

Figure 1.2 Example of Anomalies

Machine Learning is used in a variety of fields, a few of which are mentioned below.

i. **Network Anomaly Detection:** Statistical machine learning is one class of statistical approaches used in the field of Network Anomaly Detection. A choice of a learning scenario depends on the information available in measurements. For example, a frequent scenario is that there are only raw network measurements available and thus unsupervised learning methods are used. If additional information is available, e.g. from network operators, known anomalies or normal network behaviors, learning can be done with supervision. A choice of a mapping depends on the availability of a model, the amount and the type of measurements, and complexity of learning algorithms[4].

ii. **Evaluating Learned Knowledge:** Rules induced from training data are not necessarily of high quality. The performance of knowledge acquired in this

way is an empirical question that must be answered before that knowledge can be used on a regular basis. One standard approach to evaluation involves dividing the data into two sets, training on the first set, and testing the induced knowledge on the second. One can repeat this process a number of times with different splits, and then average the results to estimate the rules' performance on completely new problems. Kibler and Langley (1988) experimental methods of this sort for a broad class of learning algorithms. An important part of the evaluation process is experts' examination of the learned knowledge. Evans and Fisher (1994) encourage an iterative process in developing a fielded application.[5]

1.4 Types of Intrusion Detection Systems

An Intrusion can be termed as any activity which is aimed at disrupting or denying a service by gaining unauthorized access. Various attacks like DDoS, Identity spoofing, Ping of Death, Buffer Overflow etc. are used to intrude and disrupt a network. Intrusion Detection Systems are used to prevent such intrusions by detecting them at an earlier stage.

All Intrusion Detection Systems use one of two detection techniques:

i. Signature Based Detection
ii. Statistical Anomaly Based Detection

1.4.1 Signature Based Detection

Signature-based IDS monitors packets in the network, and compares them with pre-configured and pre-determined attack patterns, known as signatures.[6]

1.4.2 Statistical Anomaly Based Detection

Anomaly based detection techniques model a “normal” scenario and any deviation from that is considered an anomaly. Anomaly based detection is preferred over Signature based detection due to their ability to detect novelty attacks.[6]

1.5 Machine Learning

Machine learning is a branch of artificial intelligence, concerned with the construction and study of systems that can learn from data. Machine learning focuses on the

development of computer programs that can teach themselves to grow and change when exposed to new data as illustrated in figure 1.3.[7]

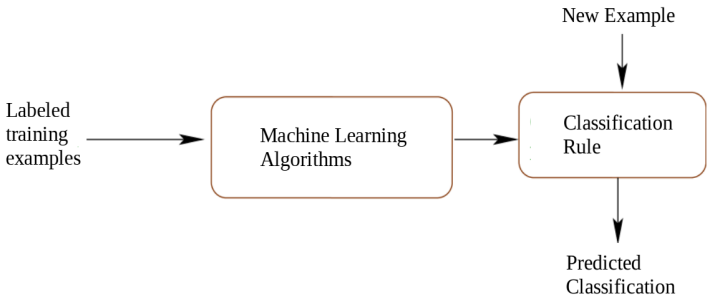


Figure 1.3 Machine Learning System

Machine learning algorithms are classified into 3 types-

i. Supervised Learning
ii. Unsupervised Learning
iii. Reinforcement Learning

1.5.1 Supervised Learning

In supervised learning, the model defines the effect one set of observations, called inputs, has on another set of observations, called outputs.[7] As shown in Figure 1.4, the inputs are assumed to be at the beginning and outputs at the end of the causal chain. The models can include mediating variables between the inputs and outputs. A supervised learning algorithm makes it possible, given a large data set of input/output pairs, to predict the output value for some new input value that you may not have seen before.

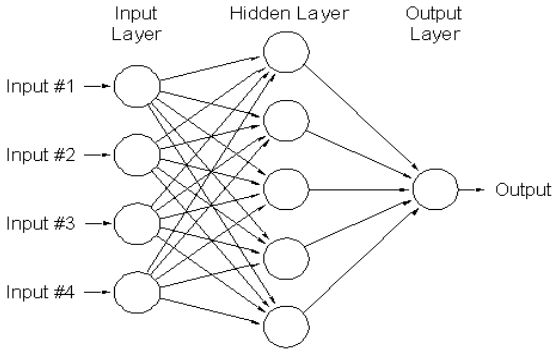


Figure 1.4 Supervised Learning Model

1.5.2 Unsupervised Learning

In unsupervised learning, all the observations are assumed to be caused by latent variables, that is, the observations are assumed to be at the end of the causal chain.[7] With unsupervised learning it is possible to learn larger and more complex models than with supervised learning. The learning can proceed hierarchically from the observations into ever more abstract levels of representation as shown in figure 1.5. Each additional hierarchy needs to learn only one step and therefore the learning time increases (approximately) linearly in the number of levels in the model hierarchy unlike supervised learning where the learning task increases exponentially. Unsupervised learning can be used for bridging the causal gap between input and output observations. The latent variables in the higher levels of abstraction are the causes for both sets of observations and mediate the dependence between inputs and outputs.

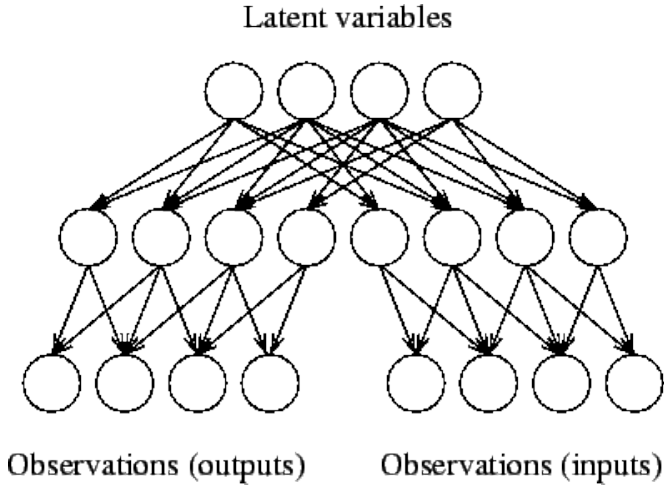


Figure 1.5 Unsupervised Learning Model

1.5.3 Reinforcement Learning

Reinforcement learning is learning what to do - how to map situations to actions - as to maximize a numerical reward signal. A Reinforcement learning agent learns from the consequences of its actions, rather than from being explicitly taught and it selects its actions on basis of its experiences (exploitation) and also by new choices (exploration), which is essentially trial and error learning as illustrated in figure 1.6.

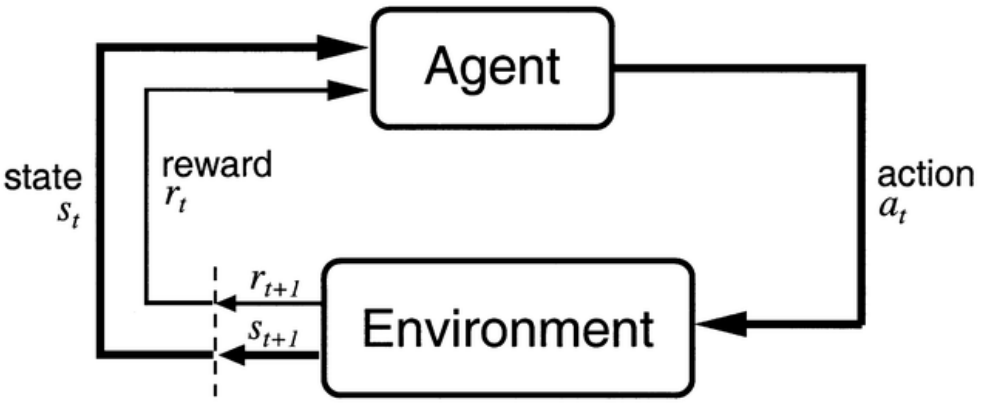


Figure 1.6 Reinforcement Learning Model

1.6 Types of Anomaly Based Detection

We now review the different techniques of Anomaly based IDS. They are classified as shown in figure 1.7. The most important ones are-

i. Statistical Anomaly Detection
ii. Data Mining Based Detection
iii. Knowledge Based Detection

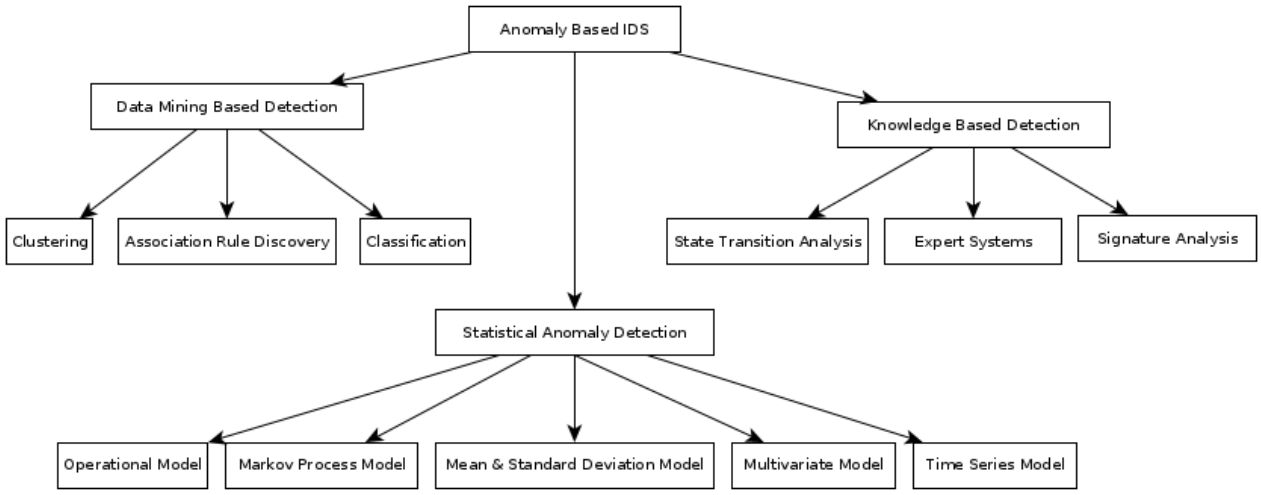


Figure 1.7 Taxonomy of Anomaly Based IDS

1.6.1 Statistical Anomaly Detection

Statistical based anomaly detection techniques use statistical properties and statistical tests to determine whether "Observed behavior" deviate significantly from the "expected

behavior". Statistical based anomaly detection techniques use statistical properties (e.g., mean and variance) of normal activities to build a statistical based normal profile and employ statistical tests to determine whether observed activities deviate significantly from the normal profile. The IDS goes on assigning a score to an anomalous activity. As soon as this score becomes greater certain threshold, it will generate an alarm.[8] Statistical Anomaly Based IDS can further be classified into the following categories-

- **Operational Model:** This model is based on the operational assumption that an anomaly can be identified through a comparison of an observation with a predefined limit. Based on the cardinality of observation that happens over a time an alarm is raised. The operational model is most applicable to metrics where experience has shown that certain values are frequently linked with intrusions. For example, an event counter for the number of password failures during a brief period, where more than say 10, suggest a failed log-in.
- **Markov Process Model:** The Markovian Model is used with the event counter metric to determine the normalcy of a particular event, based on the events which preceded it.[8] The model characterizes each observation as a specific state and utilizes a state transition matrix to determine if the probability of the event is high (normal) based on the preceding events. This model is basically used in two main approaches: Markov chains and Hidden Markov models. A Markov chain keeps track of an intrusion by examining the system at fixed intervals and maintains the record of its state. If the state change takes place it computes the probability for that state at a given time interval. If this probability is low at that time interval then that event is considered as an anomalous.
- **Mean and Standard Deviation Model:** The Mean and Standard Deviation Model is based on the traditional statistical determination of the normalcy of an observation based on its position relative to a specified confidence range.[8] In this sub-model, event that falls outside the set interval will be declared as an anomalous.
- **Multivariate Model:** This model can be applied to intrusion detection for monitoring and detecting anomalies of a process in an information system.[8] This model is

similar to the mean and standard deviation model except that it is based on correlations among two or more features. This model would be useful in the situation where two or more features are related. This model permits the identification of potential anomalies where the complexity of the situation requires the comparison of multiple parameters.

- **Time Series Model:** The Time Series Model, attempts to identify anomalies by reviewing the order and time interval of activities on the network.[8] If the probability of the occurrence of an observation is low, then the event is labeled as abnormal. This model provides the ability to evolve over time based on the activities of the users. Anomalies in time series data are data points that significantly deviate from the normal pattern of the data sequence.

1.6.2 Data Mining Based Approach

As IDS can only detect known attacks, but it cannot detect insider attacks, the better solution for an IDS can be Data Mining at its core and is defined as "the process of extracting useful and previously unnoticed models or patterns from large data stores".[8] The data-mining process tends to reduce the amount of data that must be retained for historical comparisons of network activity, creating data that is more meaningful to anomaly detection.

Data Mining based approach is classified into following techniques:

- **Clustering:** Clustering[8] is an unsupervised technique for finding patterns in unlabeled data with many dimensions (number of attributes). Mostly k-means clustering is used to find natural groupings of similar instances. Records that are far from any of these clusters indicate unusual activity that may be part of a new attack.
- **Association Rule Discovery:** Association rules mining finds correlation between the attributes. This technique was initially applied to the so-called market basket analysis, which aims at finding regularities in shopping behavior of customers of supermarkets. This method is usually very slow and its being replaced by other powerful techniques like clustering and classification.[8]

- **Classification:** Classification[8] is one of the main techniques used in data mining. Its main goal is to learn from class-labeled training instances for predicting classes of new or previously unseen data. Instances in the training set have labels. New data is classified based on the training set. Basically a classification tree (also called as decision tree) is built to predict the category to which a particular instance belongs.

1.6.3 Knowledge Based Detection Techniques

Knowledge based detection Technique[8] can be used for both signature based IDS as well as anomaly based IDS. It accumulates the knowledge about specific attacks and system vulnerabilities. It uses this knowledge to exploit the attacks and vulnerabilities to generate the alarm. Any other event that is not recognized as an attack is accepted. Therefore the accuracy of knowledge based intrusion detection systems is considered good. Knowledge based detection Technique can further be classified as:

i. **State Transition Analysis:** This technique describes the attacks with a set of goals and transitions, and represents them as state transition diagrams.[8] State transition diagram is a graphical representation of the actions performed by an intruder to archive a system compromise. In state transition analysis, an intrusion is viewed as a sequence of actions performed by an intruder that leads from some initial state on a computer system to a target compromised state. State transition analysis diagrams identify the requirements and the compromise of the penetration. They also list the key actions that have to occur for the successful completion of an intrusion.

ii. **Expert Systems:** The expert system[8] contains a set of rules that describe attacks. Audit events are then translated into facts carrying their semantic significance in the expert system, and the inference engine draws conclusions using these rules and facts. This method increases the abstraction level of the audit data by attaching semantic to it. It also encodes knowledge about past intrusions, known system vulnerabilities and the security policy. As information is gathered, the expert system determines whether any rules have been satisfied.

iii. **Signature Analysis:** Signature analysis follows exactly the same knowledge-acquisition approach as expert systems, but the knowledge acquired is exploited in a different way.[8] The semantic description of the attacks is transformed into information that can be found in the audit trail in a straightforward way. For example, attack scenarios might be translated into the sequences of audit events they generate, or into patterns of data that can be sought in the audit trail generated by the system.

CHAPTER 2

LITERATURE SURVEY

Chapter 2

LITERATURE SURVEY

The existing literature regarding intrusion detection systems as well as machine learning algorithms are discussed below. Additionally the theoretical details of Hidden Markov Models and Naive Bayes Classifier are explained.

2.1 Statistical Modeling

The formalization of relationships between variables in the form of mathematical equations results in a **Statistical Model**. It describes how random variables are related to each other. The model is statistical as the variables are not deterministically but rather stochastically related.

2.1.1 Markov Models

In order to understand the definition of a Markov Model, a clear definition of the mathematical principle known as Markov Property must be established. A stochastic process has the Markov property if the conditional probability distribution of future states of the process depends only upon the present state, rather than on the sequence of events that preceded it.

In other words, a Markov Model is used mainly to analyze temporal data, and it assumes that the future is independent of the past states, and is dependent only on the data contained in the present state. Given the following set $D = \{X_1 ... X_n\}$, we can say X_t depends on $X_{t-1} ... X_{t-m}$ with the simplest case being m=1. We further simplify our model by assuming discrete time and space of the sets.[9]

The most common Markov models and their relationships are summarized in the following table 2.1:

	Fully Observable System States	**Partially Observable System States**
Autonomous System	Markov Chain	Hidden Markov Model
Controlled System	Markov Decision Process	Partially Observable MDP

Table 2.1 Markov Models and their relationships

2.1.2 Markov Chains

Markov chains are used to model autonomous systems whose states are fully observable. Discrete random variables $X_1 ... X_n$ form a Markov Chain, if they respect

$$P(X_t|X_1 ... X_{t-1}) = P(X_t|X_{t-1})$$

The above equation is illustrated in figure 2.1 as:

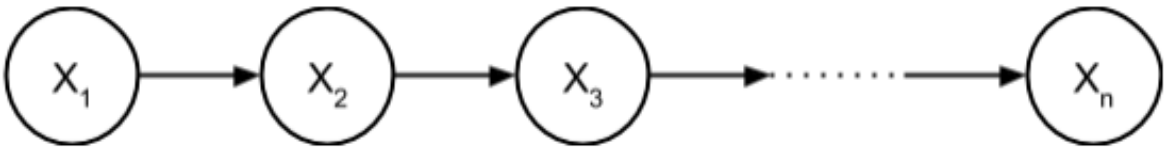


Figure 2.1 Markov Chain Illustration

The biggest drawback of Markov Chains is that it is assumed that the whole system is visible. This assumption is invalid in several real-life scenarios as more often there are two different types of states/variable namely observable variables and hidden variable. Hidden variables are also known as latent variables.

2.1.3 Hidden Markov Model

To overcome the disadvantage of Markov Chains, the concept of Hidden Markov Models (HMM) is used. Hidden Markov Models are useful to define an autonomous stochastic model whose states are partially observable. The concept of HMM is as illustrated in the **Trellis Graph** shown in figure 2.2:

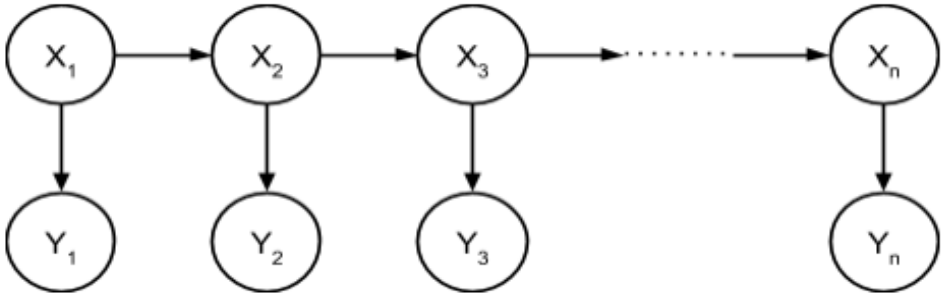


Figure 2.2 Trellis Graph Representation of a HMM

In the above graph, there are two types of states. The hidden/latent variables are represented as,

$$X_1 ... X_n \in \{1...m\}$$

The visible states, which are observable, are represented by

$$Y_1 ... Y_n \in \chi \text{(discrete/finite variables)}$$

There are three parameters under consideration under Hidden Markov Models.

i. **State Transition Probability Matrix:** The probability of the HMM transitioning from an existing state X_k to a new state X_{k+1}. It is formally defined as
$A_{ij} = P(X_{k+1} = j | X_k = i) \forall (i, j\{1...m\})$

ii. **Emission Probability:** The probability of a given observable variable Y_k occurring given the probability of a latent variable X_k. It is a **probability mass function**, as we are considering only discrete random variables. It is formally defined as
$B_i(y) = P(Y_k = y | X_k = i) \forall (i \in \{1...m\}, x \in \chi)$

iii. **Initial Distribution Probability:** The probability that a given HMM is in an initial state X_k. It is formally defined as
$\pi_i = P(X_k = i) \forall (i \in \{1...m\})$

Given the above three parameters, it is possible to formally define HMM's as follows: A Hidden Markov Model (λ) is a five tuple as given: $(\lambda) = [X, Y, A, B, \pi]$, with the joint probability distribution of X and Y defined as,

$$P(Y_1 ... Y_n, X_1 ... X_n) = P(X_1) P(Y_1 | X_1) \prod_{k=2}^{n} P(X_k | X_{k-1}) P(Y_k | X_k)$$

There are three problems associated with Hidden Markov Models. These are commonly used to analyse and obtain useful information from the HMM. The three problems are as described.

i. **Evaluation** of the probability that a given model generate a given sequence of

ii. **Decoding** the sequence of the hidden states that most likely generated a given sequence of observations. The **Viterbi Algorithm** solves this problem.

iii. **Learning** the model which most probably underlies the given sample of observations. In other words, learning the parameters of the HMM. This problem is solved using the **Baum-Welch Algorithm**.

2.1.4 HMM Based Related Work

i. **Adaptive Network Intrusion Detection System Using a Hybrid Approach:** In this approach, an adaptive network intrusion detection system, that uses a two stage architecture is described. In the first stage a probabilistic classifier is used to detect potential anomalies in the traffic. In the second stage a HMM based traffic model is used to narrow down the potential attack IP addresses. Due to the difficulties that arise when implementing HMM in real time, HMM model along with NB model was incorporated into a hybrid model for intrusion detection[10]. The proposed hybrid model performed well in detecting intrusions. HMM with more than five states had 100% accuracy classifying all IPs from CAIDA[11] as attack and IPs from DARPA[12] as clean. When tried with HMM with less than five states, few of the attacking streams were classified as clean traffic. This is due to the inability of HMM with very few states to model the data accurately. Using HMM with larger states gave exact results and the number of states to be chosen for a server can be computed empirically.

ii. **Sensing attacks in Computers Networks with Hidden Markov Models:** In this approach,[13] an Intrusion Detection model for computer networks based on Hidden Markov Models is proposed. The proposed model aims at detecting intrusions by analysing the sequences of commands that flow between hosts in a network for a particular service (e.g., an ftp session). For each command sequence, a probability value is assigned and a decision is taken according to some predefined decision threshold. First the system must be trained in order to learn the typical sequences of commands related to innocuous connections. Then, intrusion detection is performed by identifying anomalous sequences. Different HMM models were investigated in

by identifying anomalous sequences. Different HMM models were investigated in terms of the dictionary of symbols, number of hidden states, and different training sets. It was found that good performances can be attained by using dictionary of symbols made up of all symbols in the training set, and adding a NaS (not-a-symbol) symbol in account of symbols in the test set that are not represented in the training set. Performances can be further improved by combining different HMM. As the size of training sets in an intrusion detection application is typically large, it was proposed to split the training set in a number of parts, training different HMM and then combining the output probabilities by three well known combination.

2.2 Naive Bayes Classifier

A Naïve Bayes Classifier is a simple probabilistic classifier which uses the Bayes' theorem with an assumption that the occurrence of an event is totally unrelated to the occurrence of another.

Despite their naive design and apparently oversimplified assumptions, Naive Bayes classifiers have worked quite well in many complex real-world situations. In 2004, an analysis of the Bayesian classification problem showed that there are sound theoretical reasons for the apparently implausible efficacy of naive Bayes classifiers.[14]

2.2.1 Bayes Theorem

Bayes theorem is used by the Naïve Bayes Classifier. It is particularly suited when the dimensionality of the inputs is high. The formula for the Bayes theorem is represented by the figure below.

$$P(W|L) = \frac{P(L|W)P(W)}{P(L)} = \frac{P(L|W)P(W)}{P(L|W)P(W) + P(L|M)P(M)}$$

where,

$P(W|L)$ →Probability of outcome W given L or "posterior probability"

$P(L|W)$ →Probability of outcome L given W or "likelihood"

$P(W)$ →Independent probability of W

$P(L)$ →Independent probability of L or "prior probability"

with a Woman and L denote the event that the conversation was held with a long-haired person. Assuming that women constitute half the population, the probability that W occurs is P (W) = 0.5.

Suppose it is also known that 75% of women have long hair, which we denote as $P(L|W) = 0.75$. Likewise, suppose it is known that 15% of men have long hair, or $P(L|M) = 0.15$, where M is the complementary event of W.

Calculation of the probability that the conversation was held with a woman, given the fact that the person had long hair, or, in our notation, $P(W|L)$ can be calculated using Bayes formula shown in the figure above.

2.2.2 Formal Definition and Background

The naive Bayes classifier applies to learning tasks where each instance x is described by a conjunction of attribute values and where the target function $f(x)$ can take on any value from some finite set V. A set of training examples of the target function is provided, and a new instance is presented, described by the tuple of attribute values $< a_1, a_2...a_n >$. The learner is asked to predict the target value, or classification, for this new instance.[15]

Assumption:

- Training set consists of instances described as conjunctions of attribute values
- Target classification is based on a finite set of classes 'V'
- Independence assumption: features are independent in a given class.

Task: Predict the correct class for a new instance $< a_1, a_2...a_n >$

Key Idea: The Bayesian approach to classifying the new instance is to assign the most probable target value, VMAP, given the attribute values $< a_1, a_2...a_n >$ that describe the instance.

$$V_{MAP} = argmax\ P(v_j|a_1, a_2, a_3...a_n)\ \forall\ v_j \in V$$

Rewriting the above equation using Bayes Theorem we get,

$$V_{MAP} = argmax\ \frac{P(a_1, a_2, a_3...a_n|v_j)}{P(a_1, a_2, a_3...a_n)}\ \forall\ v_j \in V$$

$$V_{MAP} = argmax\ P(a_1, a_2, a_3...a_n|v_j)P(v_j)\ \forall\ v_j \in V$$

The naive Bayes classifier is based on the simplifying assumption that the attribute values are conditionally independent given the target value. The probability of observing the conjunction <a1, a2… an> is just the product of the probabilities for the individual attributes. That is,

$$V_{MAP} = argmax\ P(a_1, a_2, a_3 ... a_n | v_j) = \prod_i^n P(a_i | v_j)$$

Hence we get the following classifier:

$$v_{NB} = argmax\ P(v_j) \sum_i^n P(a_i | v_j)$$

where,

$v_{NB} \rightarrow$ target value output by the NBC.

2.2.3 Properties of Naive Bayes

The properties of Naive Bayes Classifier are:

- **Incremental approach:** With each training example, the prior and the likelihood can be updated dynamically. This results in a flexible and a robust model.
- **Combines prior knowledge and observed data:** The prior probability of a hypothesis multiplied with a probability of the hypothesis given the training data leads to more accuracy in correct classification.
- **Probabilistic hypothesis:** The output obtained is not just the classification but also a probability distribution over all classes.
- **Meta-Classification:** The outputs of several classifiers can be combined by multiplying the probabilities that all classifiers predict for a given class.

2.2.4 Advantages and Limitations

In this section we discuss the various advantages and disadvantages of the Naïve Bayes classifier.

Advantages are:

- Naïve Bayes Classification is computationally fast and space efficient

- It is faster to train the classifier as it requires a single scan
- It is not sensitive to irrelevant data
- It handles streaming data well

Disadvantages are:

- Requires several records to obtain good results
- When a predictor category is not present in the training data, naive Bayes assumes that a record with that category of the predictor has zero probability. This can be a problem if this rare predictor value is important.

2.2.5 Recent Research in Network Anomaly Detection in NBC

- **A System Approach to Network Modeling for DDoS Detection using a Naive Bayesian Classifier by R Vijayasarathy, S V Raghavan and Balaraman Ravindran:** In this paper, the authors discuss a practically realized system to detect DoS attacks using a Naive Bayesian Classifier. They have modeled the network for two protocols – TCP and UDP. The concept of windowing is used to have a reasonable estimate and control over the reaction time of the system for attacks and better modeling from larger datasets.[16] Three datasets were used in the experiment, namely, DARPA dataset, SETS (TCP) dataset and SETS (UDP) dataset. To determine four parameters i.e. false positives, false negatives, true positives, true negatives, they performed two tests: False Positive Test (FPT) and False Negative Test (FNT). They have calculated critical system parameters namely, Accuracy, False Alarm Rate and Miss Rate. The results of these tests are represented in figure 2.3 They report improvements in accuracy with increase in window size.

  The concept of windowing, formation of bands and grouping of packets based on TCP flags was incorporated into the proposed system. For the grouping of likely events, the Jump Clustering Algorithm was used as suggested by the author.

WS	DARPA at t =1%			SETS at t =5%		
	Acc	FAR	MR	Acc	FAR	MR
50	98.3%	2.3%	0	97%	7%	0
100	98.6%	2%	0	97.4%	6.2%	0.06%
200	98.7%	1.8%	0	97.1%	5%	1.1%

Figure 2.3 Experimental Results for TCP

- **From Feature Selection to Building of Bayesian Classifiers: A Network Intrusion Detection Perspective by Kok-Chin Khor, Choo-Yee Ting and Somnuk-Phon Amnuaisuk:** In this paper, the authors proposed a novel approach to select important features by utilizing two selected feature selection algorithms utilizing filter approach. Extra features were added into the final proposed feature set. They then constructed three types of BN namely, Naive Bayes Classifiers (NBC), Learned BN and Expert-elicited BN by utilizing a standard network intrusion dataset. The performance of each classifier was recorded. They found that there was no difference in overall performance of the Bayesian Networks and therefore, concluded that the BNs performed equivalently well in network attacks.

  The classification of attacks was well portrayed in this paper. Various attacks like DoS, Probe, R2L and U2R were used in the experiment. Also, the different methods of detecting these attacks was articulated. The proposed system will concentrate on the DDoS attacks using a Naive Bayes Classifier.

Category	NBC	BN	EE	Wenke lee
Normal	96.7	99.8	97.5	N/A
DoS	99.3	99.9	99.2	79.9
Probe	93.5	89.4	93.0	97
R2L	92.8	91.5	86.8	75
U2R	55.8	69.2	69.2	60

Figure 2.9 Comparison of Classification Results of various

BN's on full dataset and Wenke Lee

- **Combining Naïve Bayes and decision tree for adaptive Intrusion Detection by Dewan Md. Farid, Nouria Harbi, and Mohammad Zahidur Rahman:** In this paper, the authors propose a new learning algorithm for adaptive network intrusion detection using Naive Bayesian Classifier and decision tree, which performs balance detection and keeps false positives at acceptable level for different types of network attacks, and eliminates redundant attributes as well as contradictory examples from training data that make the detection model complex. The proposed algorithm also addresses some difficulties of data mining such as handling continuous attribute, dealing with missing attribute values, and reducing noise in training data.

  The authors tested the performance of their proposed algorithm with existing learning algorithms by employing on the KDD99 benchmark intrusion detection dataset.

- **An empirical study of the Naive Bayes Classifier by Irina Rish :** In this paper, Monte Carlo simulations were used to conduct a systematic study of classification accuracy for several classes of randomly generated problems. It also analyzes the impact of the distribution entropy on the classification error, showing that low-entropy feature distributions yield good performance of Naïve Bayes. It also shows that the Naive Bayes works with both independent features and functionally dependent features.

  The most important part that the paper discusses is the characteristics of the input data and its effect on the Naive Bayes classifiers performance. The author presents a challenge that the accuracy of the performance depending on the features in a NBC can only be proved my practical implementation of the NBC and proving it with specific inputs. With this, the proposed system has safely assumed these assertions and will be using the Naive Bayes Classifier without a distinction between independent assumptions and functionally dependent assumptions.

- **Adaptive Network Intrusion Detection System using a Hybrid Approach by R Rangadurai Karthick, Vipul P. Hattiwale, Balaraman Ravindran:** In this paper, the authors discuss Intrusion Detection Systems in detail and their role in the detection of DDoS attacks. They assert that two key criteria should be met by an IDS for it to be effective: (i) ability to detect unknown attack types, (ii) having very less miss classification rate. They also describe an adaptive network intrusion detection system, that uses a two stage architecture. In the first stage a probabilistic classifier is used to detect potential anomalies in the traffic. In the second stage a HMM based traffic model is used to narrow down the potential attack IP addresses.

  Considering the first phase proposed in this paper, the proposed system implements only the online classification phase. This is achieved only by implementing a Naive Bayes Classifier for the incoming network traffic. The classifier will classify the incoming traffic into either attack or normal based on the training data.

2.3 Proposed System

Researchers are trying to build a fool-proof system which can be used to detect anomalies. The current systems haven't achieved a satisfactory detection rate. Constantly working to counter challenges encountered in the field of network anomaly detection is imperative. Through our proposed system, we plan to increase the existing accuracy and to contribute to the field of Network Security. The proposed system also introduces new challenges in the field of anomaly detection.

CHAPTER 3

SYSTEM ANALYSIS

Chapter 3

SYSTEM ANALYSIS

The hardware and software details, functional requirements and the input to the proposed system is outlined in this chapter. The input details consist of the dataset statistics and the parsing techniques used.

3.1 Requirements

The different hardware and software requirements are covered in the next sub-sections. In the subsequent section, we cover the various functional requirements.

3.1.1 Hardware Requirements

- i386 or x64 based Processor
- 50 GB Secondary storage
- 8 GB of RAM

3.1.2 Software Requirements

- GNU/ Linux based OS
- Python 2.6 or greater
- Pycharm community edition
- Numpy 1.7 or greater
- Wireshark
- Git
- Flask
- Matplotlib
- Firefox or Chrome browser

3.1.3 Functional Requirements

Common functional requirements of an Intrusion Detection System are discussed below.

a) The IDS must continuously monitor and report intrusions.

b) The IDS should be modular and configurable as each host and network segment will

require their own tests and these tests will need to be continuously upgraded and eventually replaced with new tests.

c) The IDS must operate in a hostile computing environment and exhibit a high degree of fault-tolerance and allow for graceful degradation.

d) The IDS should be adaptive to network topology and configuration changes as computing elements are dynamically added and removed from the network.

e) Anomaly detection systems should have a very low false alarm rate.

f) The IDS should be capable of providing an automated response to suspicious activity.

g) The ability to detect and react to distributed and coordinated attacks.

h) The IDS should be able to work with other Commercial Off-the-Shelf (COTS) security tools, as no vendor toolset is likely to excel in or to provide complete coverage of the detection, diagnosis, and response responsibilities.

i) IDS data often requires additional analysis to assess any damage to the network after an intrusion has been detected.

3.2 Dataset

The IDS is trained and tested with standard datasets like DARPA[19], KDD[20] and Auckland[21]. Each dataset is a collection of network packets grouped to form **tcpdump** files. Of the different types of packets in the tcpdump files, we filter only **TCP** packets. The structure of a TCP packet is shown in figure 3.1.

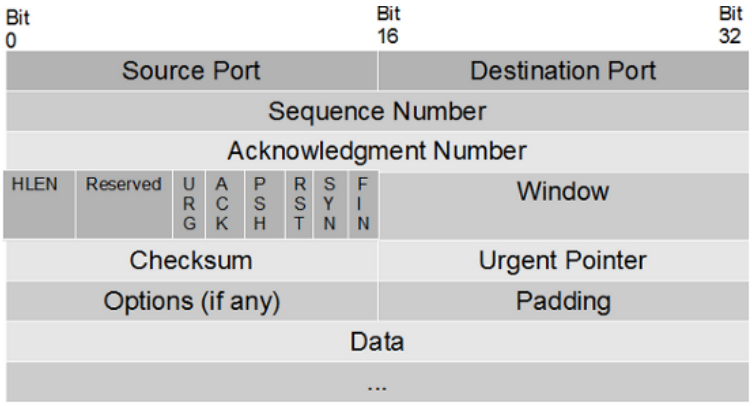


Figure 3.1 TCP Packet Format

Each TCP packet consists of TCP flags like URG, ACK, PSH, RST, SYN and FIN. We filter the flags and group them into six categories as follows in table 3.1:

Type	Flag Set	Flag Name	Description
T1	RST	Reset flag	This flag is set when the remote host rejects the incoming packet from a client on account of trying to establish a connection. This indicates that the remote host has **reset** the connection
T2	SYN	Synchronization flag	This flag is set when the host is trying to establish a connection by sending **SYN** (synchronize) packets
T3	ACK	Acknowledgement flag	This flag is set to **acknowledge** the successful receipt of packets
T4	FIN/ACK	Finish & Acknowledgement flag	This flag is set when the destination host wants to close the connection with the source host after data transfer. The FIN flag is set to indicate **termination** of connection while the ACK flag is set to acknowledge the last packet received during data transfer
T5	PSH/ACK	Push & Acknowledgement flag	This flag is set when feedback is required immediately from the client and server instead of waiting for the buffer to become full before transmission. The data is **immediately pushed** when the PSH flag is set and the ACK flag is set to acknowledge the data received
T6	Others	Others	Any **other flag/s** set other than the above mentioned flags, fall under this category

Table 3.1 TCP Flag Groups

The flags are stored as hexadecimal values which are passed to the program for classifying the incoming traffic as legitimate or malicious. In order to extract only the TCP flags from the datasets we run the following commands -

- ***tcpdump -r inside/w1mon.tcpdump -w test.pcap***

  This command is used to read the data present in a tcpdump file (w1mon.tcpdump) and write the contents to a pcap file (test.pcap)

- ***tshark -r test.pcap -Y tcp -T fields -E separator=/s -e ip.dst -e tcp.dstport -e tcp.flags > op_mon***

  This command takes test.pcap file as input, filters the tcp packets, extracts destination IP, destination port and TCP flags and stores the output in op_mon

- ***cat op_mon | grep "172.16.112.50 23" | cut -d " " -f 3 > op_flag_mon***

  This command selects the particular IP and cuts the third field which contains TCP flag set and stores the output in op_flag_mon

- ***rm op_mon***

  This command removes the intermediate file created

Finally, we get the TCP flags in the form of Hexadecimal values which are used to train and test the IDS.

The following table 3.2 consists of information about the number of attack windows and normal windows present in the dataset files considered to train and test the IDS.

	Normal Windows	**Attack Windows**
darpaTrain	219600	0
darpaNoAttack	61400	0
darpaAttack	37100	37100
kddTrain	216900	0
kddNoAttack	126400	0
kddAttack	58200	58200
aucklandTrain	219600	0
aucklandNoAttack	126400	0
aucklandAttack	393	2048

Table 3.2 Window statistics of the dataset files

CHAPTER 4

SYSTEM DESIGN

Chapter 4

SYSTEM DESIGN

System design is the process of defining the architecture, modules, components, interfaces and the data for the system to satisfy specified requirements. It pertains to the abstract representation of the data flows, inputs and outputs of the system.

4.1 Design Considerations

In this section, we consider the different modules under consideration, use-case diagram, sequence diagram, data flow diagram and state diagram.

4.1.1 Modules

The system is comprised of five modules as illustrated in figure 4.1. They are -

- Control Unit (CU)
- Traffic Capture Module (TCM)
- Learning Module (LM)
- Detection Module (DM)
- Mitigation Module (MM)

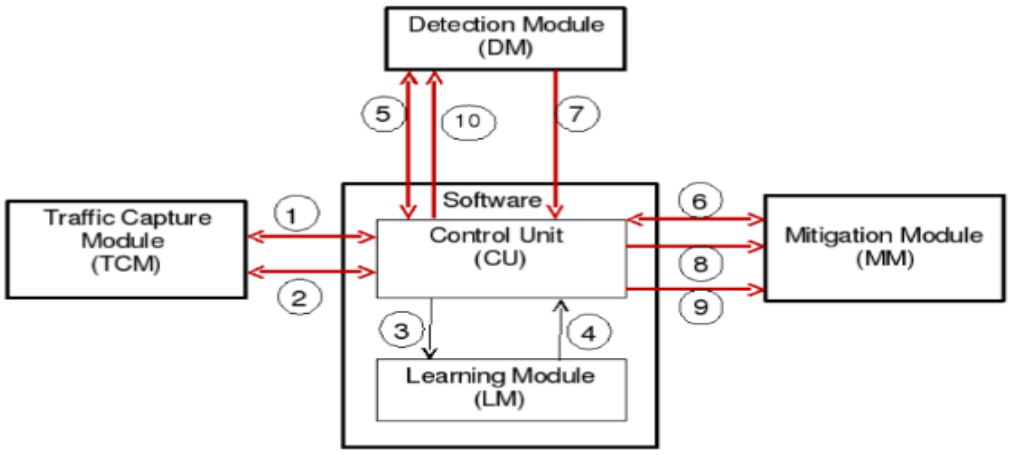


Figure 4.1 Overall System Design

Control Unit (CU):

The Control Unit is a software module, which centrally manages communication between the rest of the modules. CU is resident on the computer, hosting the Learning Module (LM), and interacts with the user (through a Graphical User Interface) to obtain inputs for the above modules. The CU also is responsible for information exchange and dissemination between the modules, and establishes a communication network between each of these modules for this purpose. The CU runs different protocols with the various modules for the task. This is a software module.

Traffic Capture Module (TCM):

The Traffic Capture Module (TCM) is a hardware module, which captures traffic required for learning phase, and computes traffic statistics as required for the Learning Module. The TCM communicates with the Control Unit (CU) to obtain it's inputs, namely stream information. Based on triggers, the values of stream configuration are loaded (by CU), traffic captured and statistics supplied back to the Control Unit.

Learning Module (LM):

The Learning Module (LM) is a software module, which resides in the host computer which is connected to the rest of the hardware modules. The LM accepts configuration details of the server targets, and learning traffic statistics (as captured by the TCM) from the CU, and arrives at model probabilities which will later be used by the Detection Module (DM) for classification of normal traffic/anomalous traffic. It is into this module that the ideas developed as a result of this research work are implemented.

Detection Module (DM):

The Detection Module (DM) is a hardware module, which on input the set of model probabilities of normal traffic per stream (output by LM, and supplied by CU), determines the state of the network (normal or abnormal) in real-time. This module is the operations module for the system. The DM talks with the CU to obtain it's inputs and interrupts the CU in case an attack flag is asserted. This will cause further action by the CU on the Mitigation Module (MM).

Mitigation Module (MM):

The Mitigation Module is a hardware module, which allows input traffic unaltered when attack flag is not set in any stream, and when attack flag is set in one or more streams, it filters traffic for the stream (s) on the basis of a white list of source IPs corresponding to the stream.

4.1.2 Use Case Diagram

Use case diagram represents a user's interaction with the system as shown in figure 4.2. It represents the dynamic aspect of the system.

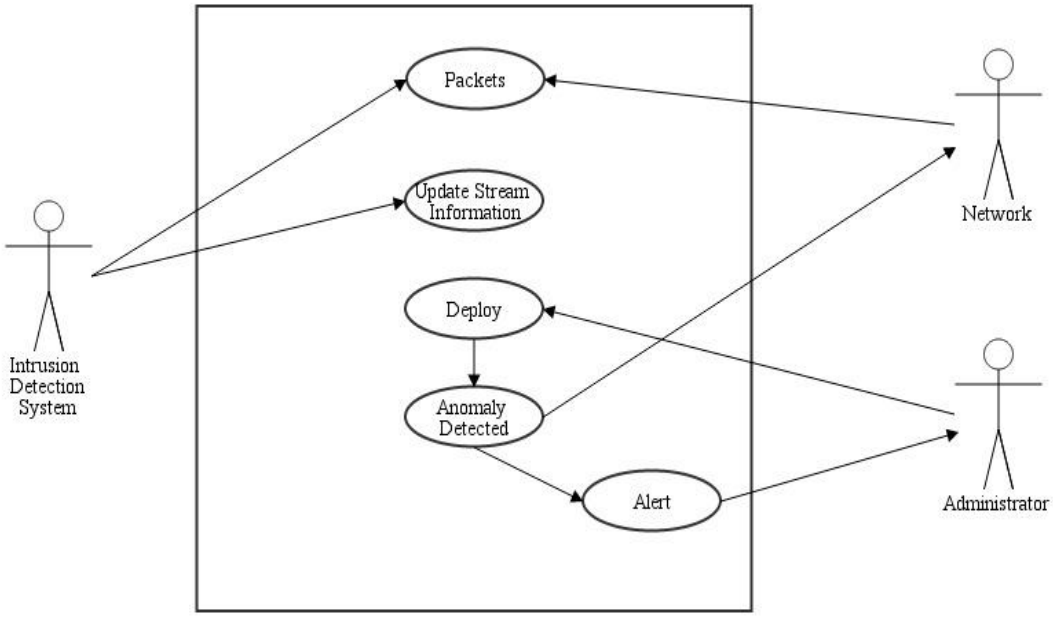


Figure 4.2 Use Case Diagram

The three actors of the system are -

- Intrusion Detection System
- Network
- Administrator

The packets are sent across the network which are accessed by the IDS to update the Stream Information. The updated stream information is used in the testing phase where, based on the incoming traffic, anomalies are detected and are notified to the administrator.

4.1.3 Data Flow Diagram

Data Flow Diagram (DFD) is a graphical representation of the flow of data through the system. A DFD shows what kind of information will be input to and output from the system, where the data will come from and go to, and where the data will be stored.

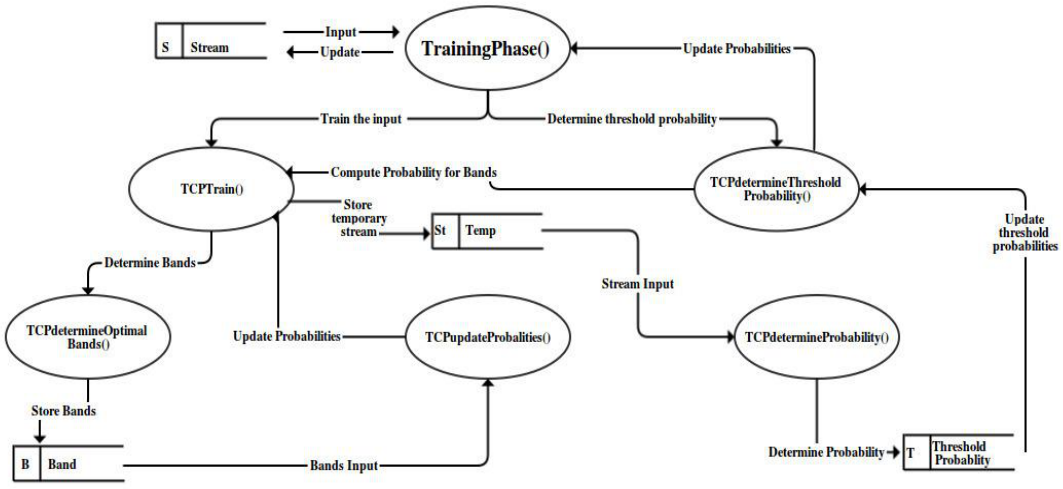


Figure 4.3 Data Flow Diagram

Figure 4.3 is a level 0 Data Flow Diagram of the system and is explained as follows. The stream S is passed as an input to the training phase. The input is used to train the model by determining bands. The bands are stored and passed as input to update the probabilities. The updated probabilities are used to determine the threshold probabilities. The threshold probabilities are updated in the stream. Once the training is done, the model is deployed and is used to identify and classify traffic as Normal or Anomalous traffic.

4.1.4 State Diagram

State diagram defines the behavior of the system as shown in figure 4.4. It gives an abstract description of the behavior of the system.

The different states are Capture Traffic, Learn, Not Under Attack and Attack. The behavior of the system is explained as follows -

1. Initially, the system is in the **Traffic Capture** state, where it captures the network traffic.
2. Once enough traffic is captured the system moves to the **Learning** state. Here, it

learns and determines the normal profile of the network.

3. When the learning process is over, the state is changed to **Not Under Attack**.
4. When an anomaly is detected, the attack flag is raised and the state changes to **Attack** state.
5. While in the Attack state, the system tries to mitigates the attack.
6. After successful mitigation, the attack flag is lowered, and the state is restored to **Not Under Attack**.

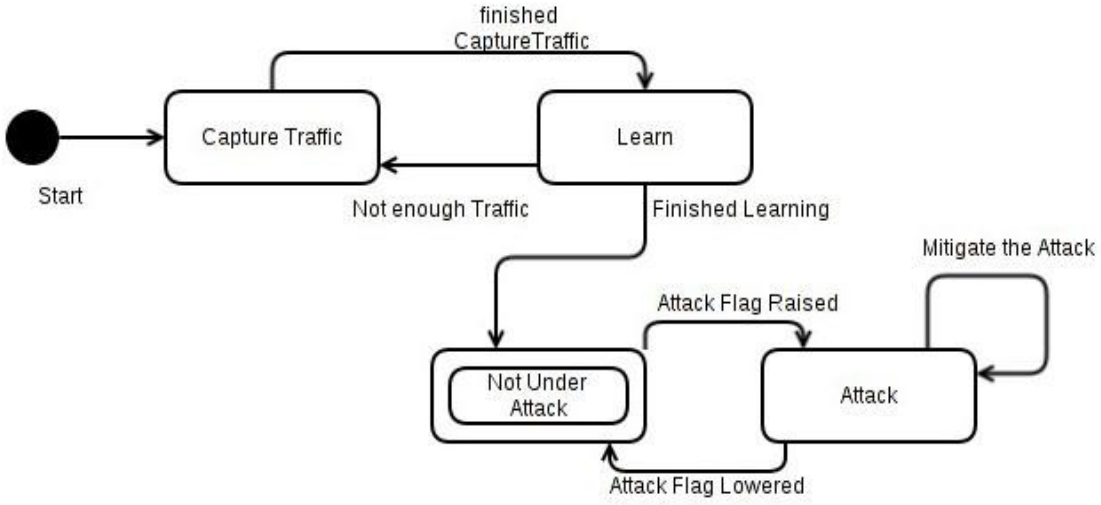


Figure 4.4 State Diagram

CHAPTER 5

IMPLEMENTATION

Chapter 5

IMPLEMENTATION

5.1 Language used for implementation

The core system of the project has been written in Python, whereas the front end contains a mix of Python, HTML and CSS.

5.1.1 Python

Python[22] is a widely used general-purpose, high-level programming language. Its design philosophy emphasizes code readability, and its syntax allows programmers to express concepts in fewer lines of code than would be possible in languages such as C. The language provides constructs intended to enable clear programs on both a small and large scale.

Python supports object-oriented, imperative and functional programming. It features a dynamic type system and automatic memory management and has a large and comprehensive standard library. Like other dynamic languages, Python is often used as a scripting language, but is also used in a wide range of non-scripting contexts. Using third-party tools, such as Py2exe or Pyinstaller, Python code can be packaged into standalone executable programs. Python interpreters are available for many operating systems.

Python is a multi-paradigm programming language: object-oriented programming and structured programming are fully supported, and there are a number of language features which support functional programming and aspect-oriented programming (including by meta-programming and by magic methods). Many other paradigms are supported using extensions, including design by contract and logic programming.

Python uses dynamic typing and a combination of reference counting and a cycle-detecting garbage collector for memory management. An important feature of Python is dynamic name resolution (late binding), which binds method and variable names during program execution. The core philosophy of the language is summarized by the document "PEP 20 (The Zen of Python)", which includes aphorisms such as:

1. Beautiful is better than ugly
2. Explicit is better than implicit

3. Simple is better than complex
4. Complex is better than complicated
5. Readability counts

Libraries like NumPy, SciPy and Matplotlib allow Python to be used effectively in scientific computing, with specialized libraries such as BioPython and Astropy providing domain-specific functionality.

5.2 Libraries used for implementation

The project uses the following libraries, which extend the functionality of Python's standard library.

5.2.1 NumPy

Arrays in Python do not have the same definition as that of in traditional programming languages like C. In C arrays are used to store data having the same data type. Python arrays also called lists are similar to C arrays except that they can be used to store mixed type of data. NumPy is an extension to the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large library of high-level mathematical functions to operate on these arrays.

NumPy[23] targets the CPython reference implementation of Python, which is a non-optimizing bytecode compiler/interpreter. Mathematical algorithms written for this version of Python often run much slower than compiled equivalents. NumPy seeks to address this problem by providing multidimensional arrays and functions and operators that operate efficiently on arrays. Thus any algorithm that can be expressed primarily as operations on arrays and matrices can run almost as quickly as the equivalent C code.

Using NumPy in Python gives functionality comparable to MATLAB since they are both interpreted, and they both allow the user to write fast programs as long as most operations work on arrays or matrices instead of scalars. In comparison, MATLAB boasts a large number of additional toolboxes, notably Simulink whereas NumPy is intrinsically integrated with Python, a more modern, complete, and open source programming language.

5.2.2 Flask

Flask[24] is a lightweight web application framework written in Python and based on the Werkzeug WSGI toolkit and Jinja2 template engine. It is BSD licensed. Flask takes the flexible Python programming language and provides a simple template for web development. Once imported into Python, Flask can be used to save time building web application.

Flask is called a micro-framework because it keeps the core simple but extensible. There is no database abstraction layer, form validation, or any other components where third-party libraries already exist to provide common functionality. However, Flask supports extensions, which can add such functionality into an application.

Flask has the following features:

1. Contains development server and debugger
2. Integrated support for unit testing
3. RESTful request dispatching
4. Uses Jinja2 for templating
5. Support for secure cookies (client side sessions)
6. 100% WSGI 1.0 compliant
7. Unicode-based
8. Extensive documentation
9. Extensions available to enhance features desired

In the project Flask's server is used to host the front-end. It listens to HTTP requests and responds to them. Based on the request it calls the various modules of the Naive Bayes Classifier and displays the results as a web page via the HTTP response.

5.2.3 Matplotlib

Matplotlib[25] is a plotting library for the Python programming language and its NumPy numerical mathematics extension. It provides an object-oriented API for embedding plots into applications. The pylab interface makes matplotlib easy to learn for experienced MATLAB users, making it a viable alternative to MATLAB as a teaching tool for numerical mathematics and signal processing.

Some of the advantages of the combination of Python, NumPy and matplotlib over

MATLAB include:

1. Based on Python, a full-featured modern object-oriented programming language suitable for large-scale software development
2. Free and open source
3. Native SVG support

5.3 Pseudo code

The pseudo code for various algorithms are mentioned in this section.

5.3.1 Determine optimal bands procedure

This module groups the events into bands. The band formation is based on the Jump clustering algorithm.

```
Function determineOptimalBands(S.W[], K)
Input: Array A = {a0..aN}, window size for stream N, number of bands K
Output: 2-dimensional array band, containing indices of per group elements in A
    1. J[N] ← {0} //store jumps between consecutive values of A
    2. Js [K − 1] ← {0} // stores the top (K − 1) jumps
    3. upper, lower, nelements ← 0
    4. I[K − 1] ← 0, Is[K − 1] ← 0
       // stores indices in A of top ((K − 1)) jumps.
    5. Sort A in descending order and copy into array As
      // Determining jumps between consecutive values of As
    6. for i = 0 to N do
    7.   J[i] ← As[i] − As[i + 1]
    8. end
    9. Determine the top K − 1 jumps from array J
    10. Store them in Js[0], Js[1] . . . Js[K − 2]
    11. Store indices of Js[0] to Js[K − 2] in J into array I
    12. Sort array I in ascending order and store in Is
    13. for i = 0 to K − 1 do
    14.   upper ← Is[i]
```

```
15.   nelements ← upper - lower + 1
16.   k ← 0
17.   band[i][k++] ← nelements
18.   for j = lower to (lower+nelements) do
19.         band[i][k++] ← index of As[j] in A
20.   end
21.   lower ← upper + 1
22. end
23. band[i][K++] ← remaining elements of A
24. return band
```

5.3.2 Update probabilities procedure

This module computes and updates the probability based on the events.

Function updateProbabilities(S, K, band, L)

Input: TCP Stream structure S, 2-D array band containing band indices of groups of A, number of bands K, Index of observable type L (for writing into appropriate index at S.W)

Output: Probabilities of events updated into corresponding W index in S

```
1. avgwcount ← 0;
  /* Increment total window to accommodate smoothing */
2. S.total windows in learning+= K;
3. for j = 0 to K do
4.   nelband ← band[j][0];
5.   for k = 1 to (1+ nelband) do
6.         avgwcount ← avgwcount + S.W[L][band[j][k]];
7.   end
     /* Smooth the event group and compute mean */
8.   avgwcount++;
9.   avgwcount ← avgwcount / nelband
     /* Write the mean value into the corresponding W indices of the
     observable type. */
10.   for k = 1 to (1+ nelband) do
11.         S.W[L][band[j][k]] ← avgwcount;
```

```
12.    end
       /* Compute probabilities */
13.   for k = 1 to (1+ nelband) do
14.         S.W[L][band[j][k]] ← S.W [L][band[j][k]] /
                                        (S.total windows in learning)
15.   end
16.   avgwcount ← 0
17. end
18. return S
```

5.3.3 Train procedure

This module trains the Naive Bayes Classifier.

Function Train(S, TF, N, K)

Input: Stream S, Traffic Statistics TF, Window size for stream S.N, number of bands S.K

Output: Updated Stream Data Structure S with learnt probabilities.

```
1. for Every window in TF do
2.    Populate S.Cis for each of the 6 Ti s
3.    for i = 1 to 6 do
      /* Update corresponding event occurrence. */
4.          Increment S.W[i][S.Ci]
5.    end
6.    Increment S.total windows in learning
7.    Reset S.Cis
8. end
/* Determine Optimal bands for each row of W, compute
probabilities */
9. for i = 1 to 6 do
10.   band ← determineOptimalBands (S.W[i],S.N,S.K)
      // Determine band ranges for row i
11.   S ← updateProbabilities(S, S.K, band, i)
      // Determine probabilities for row i
```

```
12. end
13. return S
```

5.3.4 Train phase procedure

This module initiates training. It calls the training module that trains the NBC against the training dataset. It also calls the module that determines the threshold probability.

```
Function Trainphase()
Input: Partially update stream structure S, Traffic statistics TF, window
size S.N, number of bands S.K, error proportion S.t
Output: Updated Stream Data Structure S with learnt probabilities and
threshold probability for stream
1. S ← Train(S, TF, S.N, S.K)
  /* Determine Threshold probability for the stream */
2. S.thresholdprobability ←
      determineThresholdProbability(S.N,TF,S.t)
3. return S
```

5.3.5 Determine probability procedure

Probability computation involves computing statistics of a window and determining the probability with which the window would have occurred in the training phase.

```
Function determineProbability(W, S)
Input: Stream with NB probabilities S, packet window statistics W
Output: Probability P of window W
1. Initialize P to 1
2. Determine counts of packets with flags of all 6 groups  T1 to T6
   and update counts C1 to C6
3. for i = 1 to 6 do
4.    P = P * S.W[i][Ci]
5. end
6. return P
```

5.3.6 Determine threshold probability procedure

This module computes the threshold probability which will be used to classify if a

particular window is either an attack window or not.

Function determineThresholdProbability(S, N, TF, t)

Input: Stream S, Window size for stream N, Traffic statistics TF, Error proportion t percent

Output: Threshold probability P_t for S

```
1. Seed Rng ()
2. parray[] ← 0
   // Grouping Learning traffic
3. Split traffic TF uniformly at random into 10 groups G1 to G10
4. for i = 1 to 10 do
5.     G ← TF − Gi
6.     B ← Gi
       /* Learn from 9/10th of traffic
7.     Stemp ← TCPTrain (SF, G)
       // Compute probability of remaining 1/10th of traffic
8.  for every window W in B do
9.     P ← determineProbability (W, Stemp)
10.   add P to parray;
11.  end
12. end
    //Sieving lower probabilities
13. result ← (t/100 * len(parray) + 1)th smallest element of parray
14. return result
```

5.3.7 Deploy procedure

This module tests the input traffic and computes if a window is clean or not.

Function Deploy(S, IT, AWC)

Input: Stream S, Input Traffic IT, Abnormal Window Count (AWC)

```
1. A ← 0;
2. for every packet window W in T do
3.     P ← determineProbability (W, S)
4.    if P < Threshold probability of S then
5.          increment A
```

```
6.      else
7.           decrement A
8.      end
9.      if A ≥ AWC then
10.          return attack
11.     end
12. end
```

CHAPTER 6

TESTING

Chapter 6

TESTING

Testing is the process of evaluating a system or its component(s) with the intent to find whether it satisfies the specified requirements or not. Testing is done in order to identify any gaps, errors or missing requirements. Testing is done at various levels and by various methods.

6.1 Testing Methods

There are many approaches available in software testing. A few of them are discussed in this section.

6.1.1 Static Testing

Static testing is a form of software testing where the software/program is not used. It involves reviewing of the code to find errors. It is not detailed but checks for the sanity of the code or algorithm. It includes reviews, walkthroughs and inspections.

6.1.2 Dynamic Testing

Dynamic testing is a form of software testing where the execution of programmed code is done with a given set of test cases. In dynamic testing, the program must be compiled and run. Unit tests, integration tests, system tests and acceptance test utilize dynamic testing.

6.1.3 White Box Testing

White box testing is a method of testing the internal structures of an application. In white box testing, an internal perspective of the system as well as programming skills are used to design test cases. It can be applied to unit, integration and system levels of the software testing process. It is usually done at the unit level.

6.1.4 Black Box Testing

Black box testing is a method of testing that examines the functionality of an application without peering into its internal structures. It can be applied to every level of testing like unit, integration and system although it is mostly used for higher level testing.

6.2 Testing Levels

A software testing strategy provides a road map for the software developer. Testing begins at the module level and works outward towards the integration of the entire computer based system. Different testing techniques are used. The commonly used testing strategies are Unit Testing, Integration Testing and System Testing.

6.2.1 Unit Testing

It is a testing method where individual units of code, set of one or more modules together with associated control data are tested to determine if they are fit to use. Test cases are defined to perform unit testing. The following are a few test cases considered-

Test Case 1: When window size (N) is lesser than the given threshold

This test case is checked by varying the value of N from its threshold value to a value significantly low. The following table summarizes the result of the test case.

Threshold Value (value of N)	**Input** (value of N)	**Expected Output** (in terms of accuracy)	**Observed Output** (in terms of accuracy)
100	40	<100%	62.5%

Table 6.1 Test Case 1

Result:The observed output is low in a practical perspective but numerically consistent.

Test Case 2: When window size (N) is greater than the given threshold

This test case is checked by varying the value of N from its threshold value to a value significantly high. The following table summarizes the result of the test case.

Threshold Value (value of N)	**Input** (value of N)	**Expected Output** (in terms of accuracy)	**Observed Output** (in terms of accuracy)
100	225	100%	100%

Table 6.2 Test Case 2

Result: The observed output matches with the expected output.

Test Case 3: When number of bands (K) is lesser than the given threshold

This test case is checked by varying the value of K from its threshold value to a value significantly low. The following table summarizes the result of the test case.

Threshold Value (value of K)	**Input** (value of K)	**Expected Output** (in terms of accuracy)	**Observed Output** (in terms of accuracy)
40	5	<100%	53.29%

Table 6.3 Test Case 3

Result:The observed output is low in a practical perspective but numerically consistent.

Test Case 4: When number of bands (K) is lesser than the given threshold

This test case is checked by varying the value of K from its threshold value to a value significantly high. The following table summarizes the result of the test case.

Threshold Value (value of K)	**Input** (value of K)	**Expected Output** (in terms of accuracy)	**Observed Output** (in terms of accuracy)
40	80	100%	100%

Table 6.4 Test Case 4

Result: The observed output matches with the expected output.

Test Case 5: When error proportion rate (t) is lesser than the given threshold

This test case is checked by varying the value of t from its threshold value to a value significantly low. The following table summarizes the result of the test case.

Threshold Value (value of t)	**Input** (value of t)	**Expected Output** (in terms of False Alarm Rate)	**Observed Output** (in terms of False Alarm Rate)
0.1	0.088	0%	1.61%

Table 6.5 Test Case 5

Result: The observed output matches closely with the expected output and acceptable.

Test Case 6: When error proportion rate (t) is greater than the given threshold

This test case is checked by varying the value of t from its threshold value to a value significantly high. The following table summarizes the result of the test case.

Threshold Value (value of t)	**Input** (value of t)	**Expected Output** (in terms of False Alarm Rate)	**Observed Output** (in terms of False Alarm Rate)
0.1	0.13	0%	0.92%

Table 6.6 Test Case 6

Result: The observed output matches closely with the expected output and acceptable.

CHAPTER 7

RESULTS

Chapter 7

RESULTS

The screenshots of the Naive Bayes Classifier and the accuracy results of the designed system are outlined below.

7.1 Screenshots

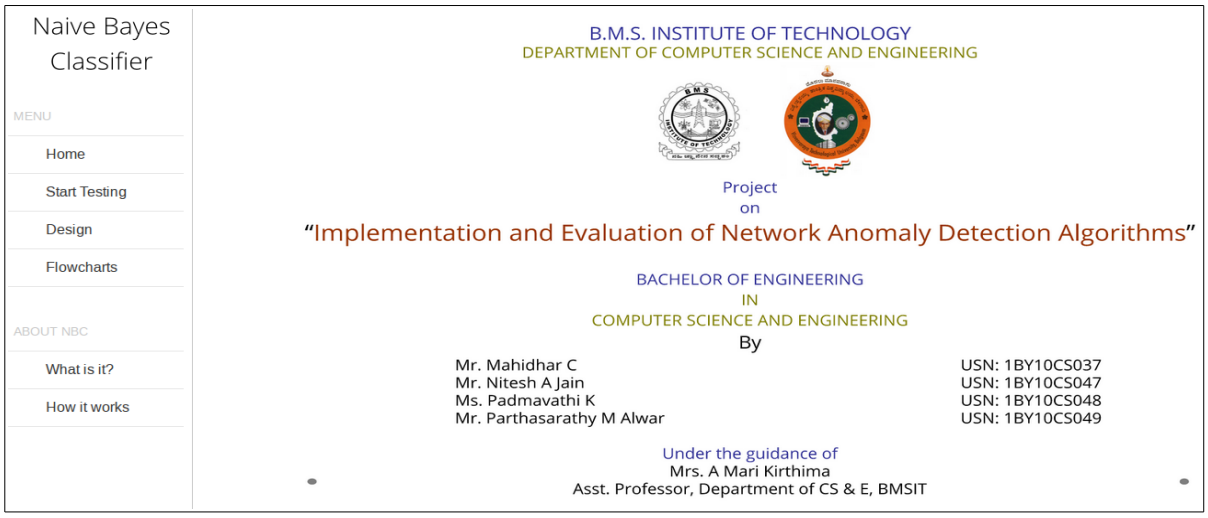


Figure 7.1 Home Page

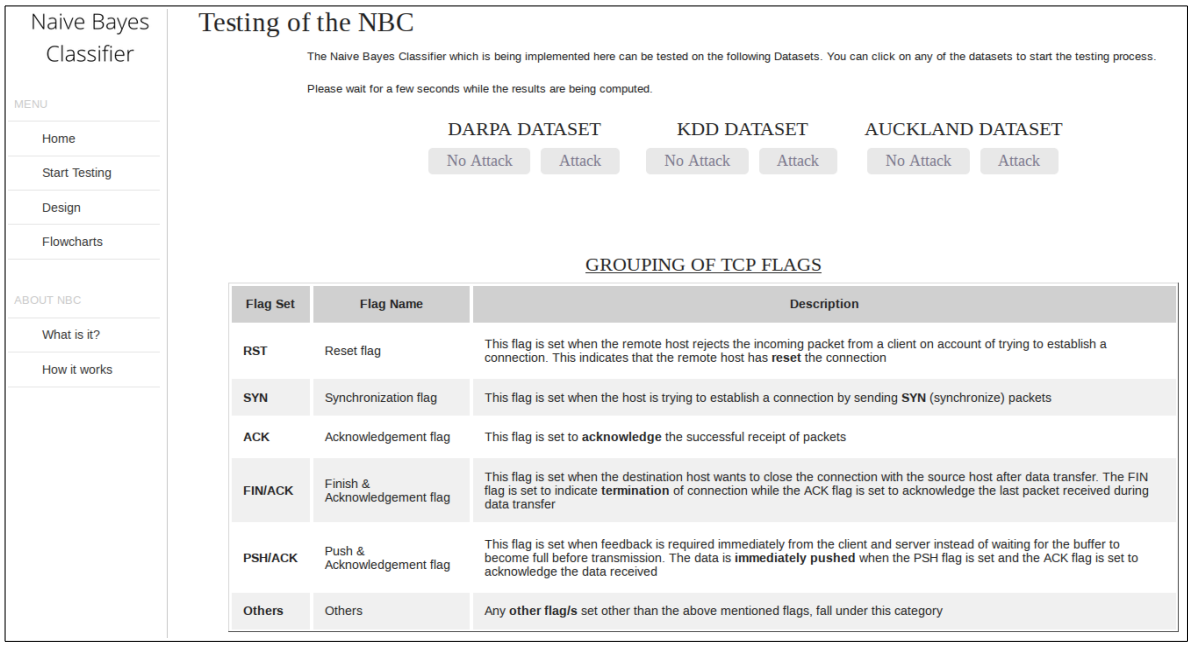


Figure 7.2 Testing Page

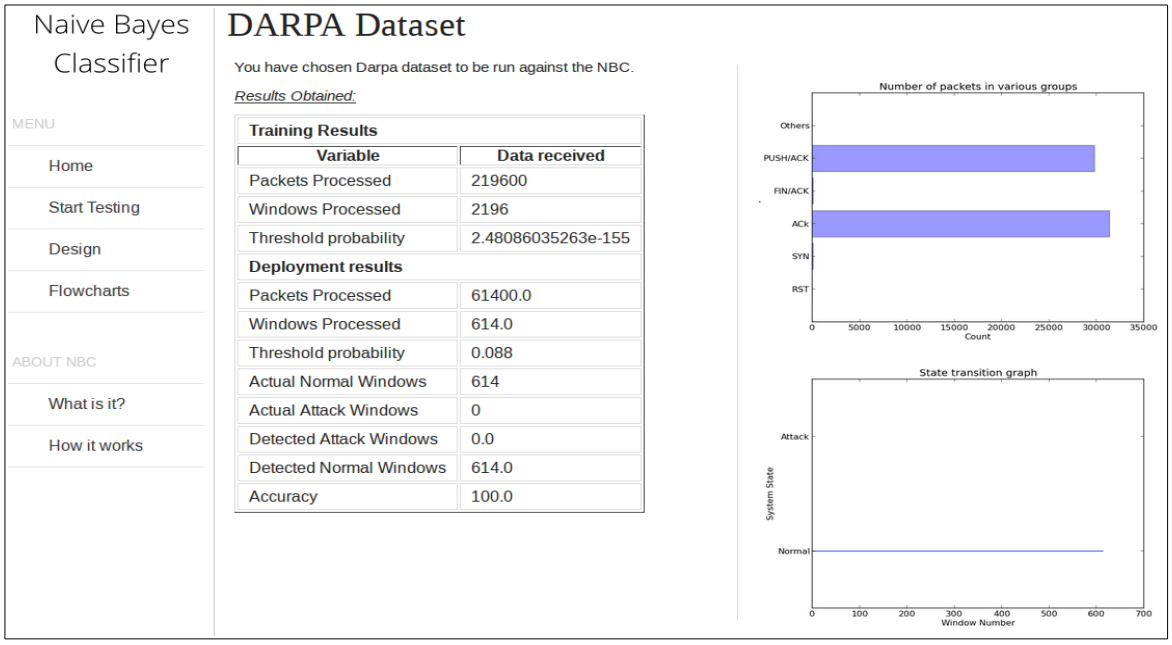


Figure 7.3 DARPA No Attack Results

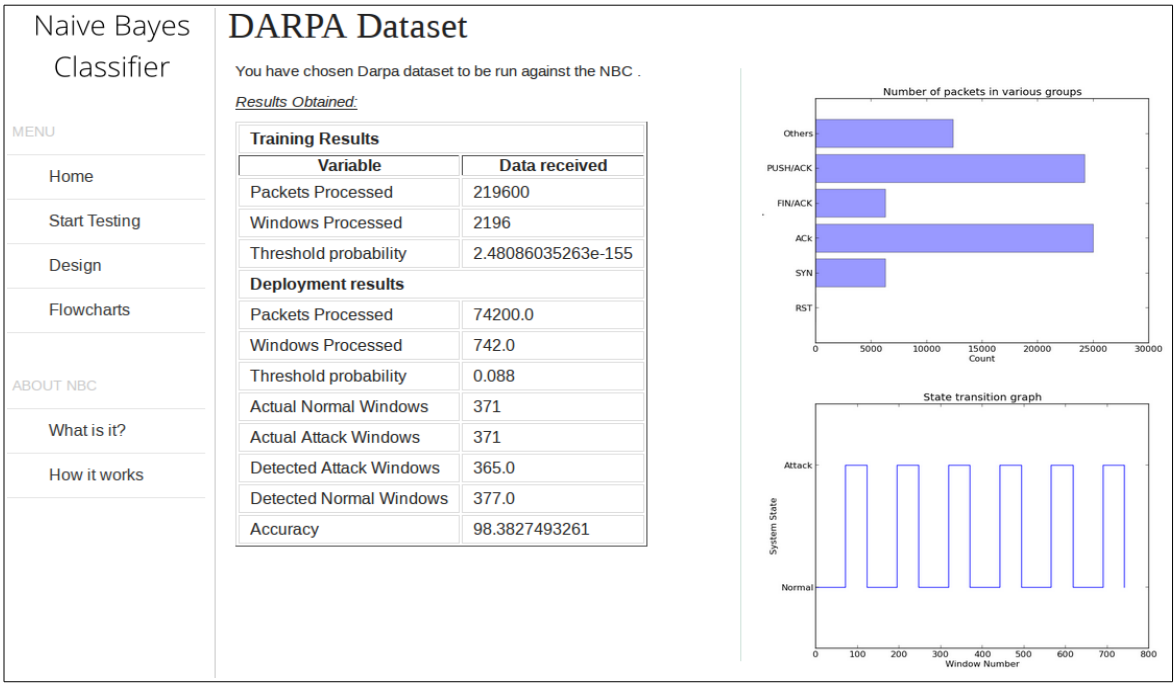


Figure 7.4 DARPA Attack Results

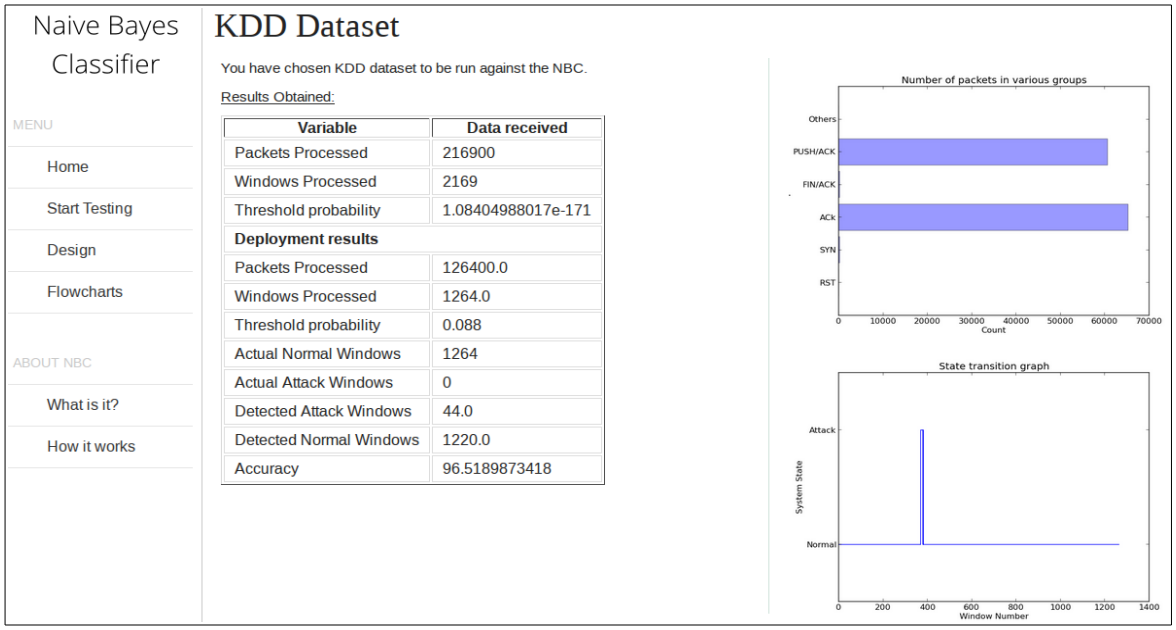


Figure 7.5 KDD No Attack Results

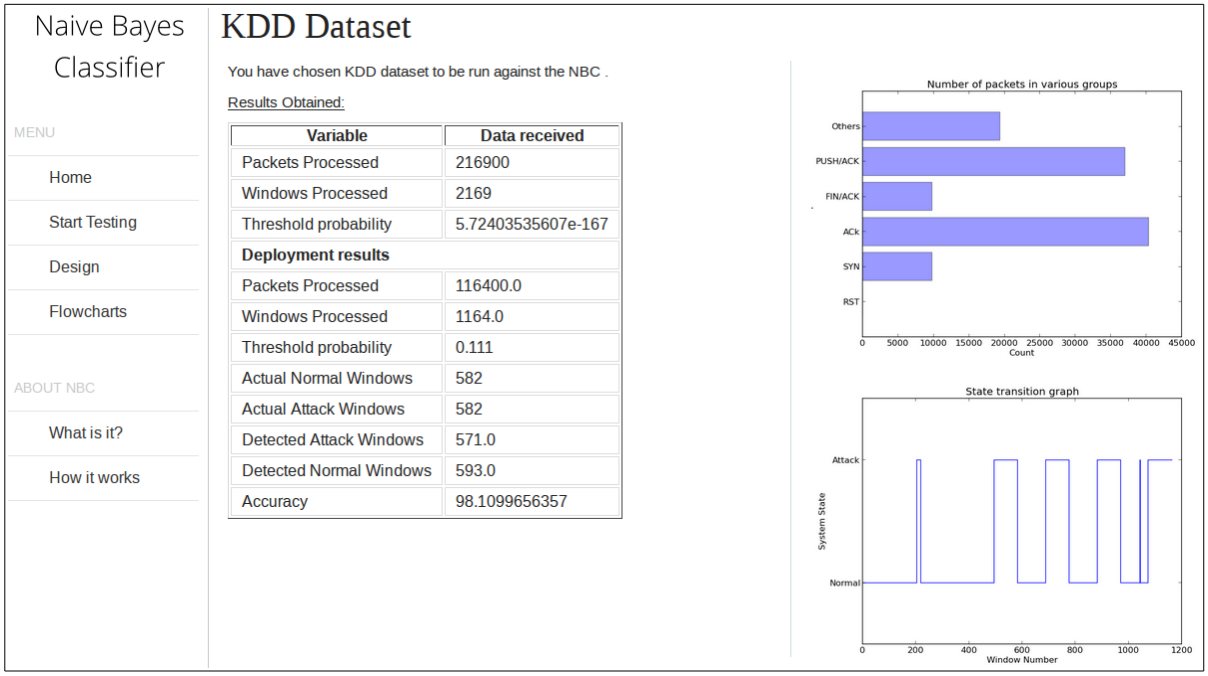


Figure 7.6 KDD Attack Results

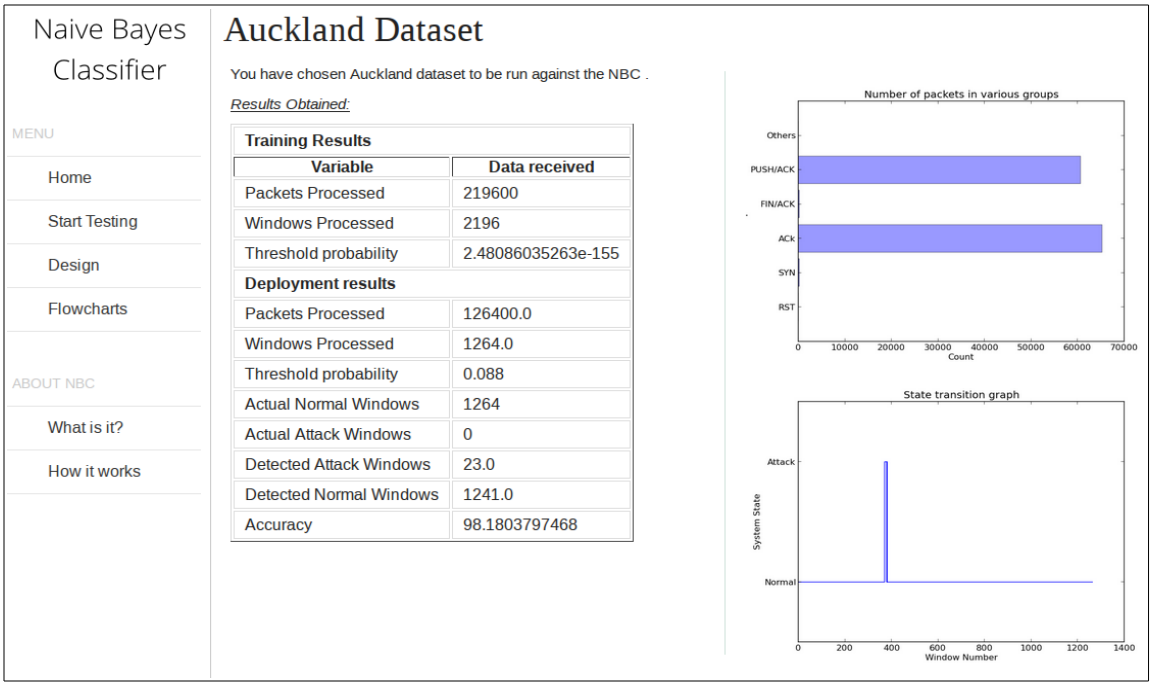


Figure 7.7 Auckland No Attack Results

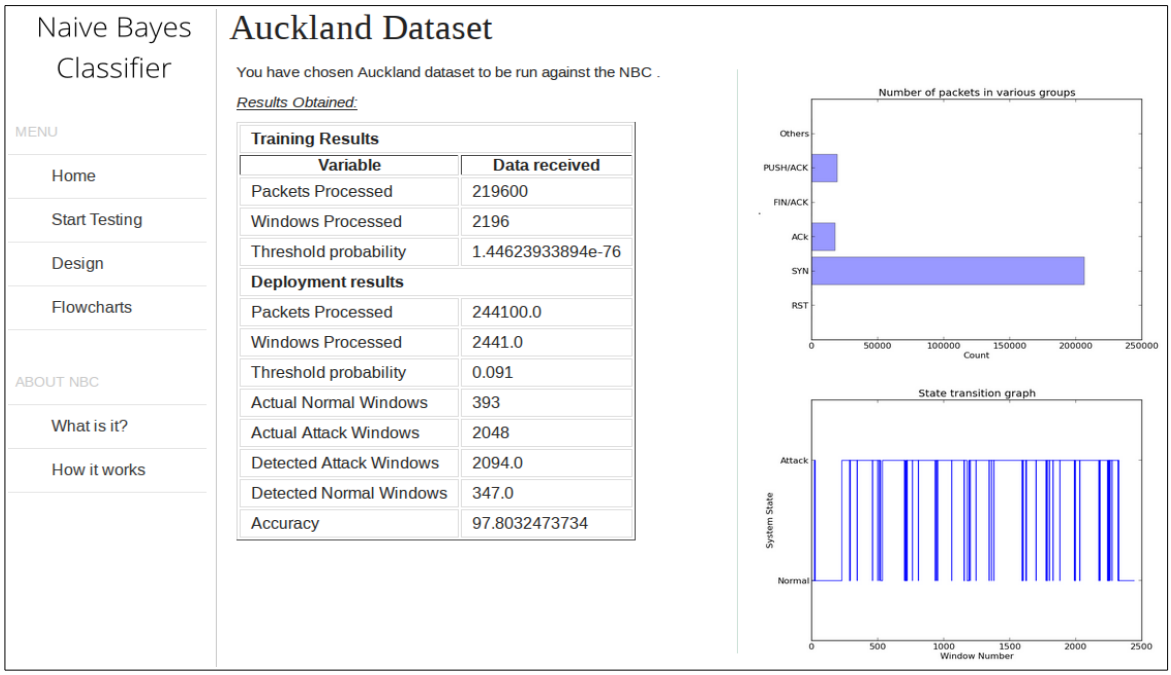


Figure 7.8 Auckland Attack Results

The different screenshots are explained in this section.

Figure 7.1 shows the first page when the application is started. This is the main page for navigating to different pages like testing, design considerations, flowcharts etc. The menu can be found on the left hand side and the certificate on the right hand side.

Figure 7.2 shows the testing page. The Naive Bayes Classifier is tested against the different datasets like DARPA, KDD and Auckland. All the three datasets contain options to run the system against a clean dataset and an attack dataset. The **"No Attack"** dataset consists of **clean** traffic used for training the classifier. The **"Attack"** dataset consists of **mixed** traffic consisting of clean traffic and attack traffic.

Figures 7.3 to 7.8 are screenshots depicting the results obtained for the DARPA, KDD and the Auckland datasets. The result page of each dataset consists of a state graph which shows the transition from **Normal State** to **Attack State** based on the incoming traffic. Also, it contains various information about the threshold probability, number of packets processed, number of attack windows detected along with various performance parameters.

7.2 Results Obtained

The Naive Bayes classifier was tested against the DARPA, KDD and Auckland -II datasets. The formula to calculate the accuracy is as follows

$$Accuracy = \frac{TP + TN}{P + N}$$

where,

TP - True Positives

TN - True Negatives

P - Number of Attack Windows

N - Number of Normal Windows

Using the above formula the accuracies for each dataset are as follows in table 7.1:

Dataset	Accuracy
DARPA	
No Attack	100%
Attack	98.38%
KDD	
No Attack	96.52%
Attack	98.11%
Auckland	
No Attack	98.18%
Attack	97.80%

Table 7.1 Results for various datasets

The window statistics of each dataset is as given in table 7.2. Each window consists of one hundred packets in this implementation. Each dataset had two types of traffic – **Clean** traffic and **Mixed** traffic. The clean traffic has no attacks whereas the mixed traffic has both clean and attack packets. The training data consists of only clean traffic, in order to build the normal profile required to detect the anomalies.

		Actual Window Count		**Detected Window Count**	
		Normal Windows	Attack Windows	Normal Windows	Attack Windows
DARPA	Train File	2196	0	NA	NA
	No Attack File	614	0	607	7
	Attack File	371	371	371	371
KDD	Train File	2169	0	NA	NA
	No Attack File	1264	0	1210	54
	Attack File	582	582	550	614
Auckland	Train File	2196	0	NA	NA
	No Attack File	1264	0	1241	23
	Attack File	393	2048	347	2094

Table 7.2 Window statistics of the datasets used

CHAPTER 8

CONCLUSION

Chapter 8

CONCLUSION

The proposed mechanism eliminates the need for a Signature Based System of detection. The advantage of not depending on a Signature Based System is that we can easily detect novelty attacks. The proposed system protects the network by constantly monitoring the TCP flags and checking for outliers. It alerts the administrator whenever in an attack state. The Naive Bayes Classifier which is implemented in this project is a "site-based", real-time system which is simplistic in its design and deployment. Testing on standard datasets such as the DARPA dataset, KDD dataset and the AUCKLAND-II dataset have shown high accuracies. The proposed mechanism can also be applied for other flag based protocols like the User Datagram Protocol. The Naive Bayes Classifier has successfully detected and alerted the administrator of a Distributed Denial of Service attack.

The accuracy of the system is calculated based on False Positives (FP) and False Negatives (FN) when tested against "No Attack" files and "Attack" files. The system has two operational phases; 1. Training Phase and 2. Testing Phase. A normal profile of the network is generated during the Training Phase. The Testing Phase is then started by using an attack/ no attack file. Based on the threshold probability obtained during the training phase, incoming packets are classified as an attack or a non-attack packet.

The proposed system has the following outcomes:

- A systems approach for DoS and DDoS detection at target using a Naive Bayes Classifier for TCP, with a design engineered for real time use and implement-ability.
- Light weight detection algorithm, with a note on processing latency and reaction time.

CHAPTER 9

CHALLENGES AND FUTURE WORK

Chapter 9

CHALLENGES AND FUTURE WORK

The model is simple and light weight in terms of detection, but while the design has been made keeping in mind flooding attacks (which form most of attacks carried out to the day), input parameters may have to be further fine tuned in order to be detecting convincingly a broader class of DoS attacks. This may involve including payload features as well. Also, at a user level, making the choice of some inputs to the system is very difficult even for an expert user. For example, it may be extremely difficult for even a seasoned network administrator to determine the right choice for the proportion of abnormal traffic in the training input, unless manual checking is done over the entire dataset.

Further more, the scalability of the model to very high volume servers has to be examined. For example, it is quite possible to see a window full of SYN packets with a high volume server, while the signature for SYN flooding attacks still remain the same. Although it may look like increasing the size of the window may solve this problem, this has to be carefully examined before a conclusion could be given. This essentially calls for testing the system with variety of traffic at various volumes.

Outside of the detection problem itself, a few other interesting areas of research surface when the intention is to build a fool proof DDoS protection system. Some of them are the following:

- Extending to other protocols. While we believe that a similar framework will work for other protocols, the research could be extended to include other protocols in the Internet protocol stack. Examples of such protocols include gateway level protocols, or application level protocols.
- Research on sound mitigation techniques. It is also to be noted that these techniques in many cases may have to be applied in-line, which calls for extremely efficient methods to handle attacks. Possible mitigation techniques include graceful degradation, cryptographic methods to stateless monitoring and making launching further attacks tougher.

APPENDIX

APPENDIX

Tuning System Parameters

After the choice of the grouping algorithm has been made, the next task is to tune system parameters in order to maximize performance. It is seen that some of these parameters could be generalized across user profiles, while the others revolve around the user traffic profile.

The following are the important system parameters in consideration:

1. Window Size (N);
2. Number of bands (K); and
3. Error Percent (t).

The optimal values for each of the above parameters were empirically determined, based on the following factors:

- Maximum Performance – lesser number of false alarms.
- Light-weight detection and quicker response – decrease response time.

Experiments on N and K

The objective of the experiment is to determine the ideal values of {N, K, t} at which the performance will be maximal. It is obvious that N and K are related to each other – K refers to the amount of compression allowed on the total number of events in the event space, which in turn, is determined by the value of N , for good performance. A higher value of N will result in more probabilities, which may (or may not) call for an increase/decrease in the value of K in order to accommodate performance requirements. But it is observed that although N and K are related to each other, the value of the two tuple {N, K} need not be tied to a particular user traffic profile, and can be generalized across user sites. However, N and K should be chosen in a way that the relation between N and K is still preserved across all user sites. On the other hand, t by definition is specific to the user traffic considered. Hence, t may have to be varied from site to site, and involves trial-and-error.

The performance is mentioned in terms of False Negatives (FN) or True Positives (TP). The parameter considered for measurement is the True Positive Rate (TPR), the ratio of

True Positive windows to the total number of Attack windows. The approach taken to finding the right {N, K, t} is as follows:

- The value of t is kept at a constant, and the system performance for different {N, K} combinations is observed to derive the relation between N and K.
- The value of t is chosen in a way that it exceeds the maximum value of t for all datasets available for experimentation. This is based on the fact that the system performance saturates at a maximum, beyond a value of t for any dataset. It is seen that t = 1% is a suitable value for the experiment. Precise values of t will be determined for every dataset separately.
- The varying values of N and K are taken from the following discrete values: N' = {50, 100, 150, 200} and K' = {5, 10, 15, 20, 30, 40}.
- A performance matrix, which describes the performance (TPR) of the system at each possible {N, K} combination from N' and K' is arrived at. The resultant matrix is a 6*4 matrix.
- The matrix is analyzed to determine {N, K} values for which performance is maximum. Bounds are determined on the values for which the system performance is guaranteed to get maximized. This will also bring to light the relation between N and K, if it is quantifiable.
- Based on the above observation, choose good values of N, K, and determine the exact value of t for every data set.

Experiment

The experiment is the same as the general experiment approach – for a chosen value of {N, K}, train with normal traffic and pass the training traffic into the testing phase in order to determine the number of False Positives. Train with normal traffic and pass the attack traffic into the testing phase, in order to determine the number of False Negatives. Determine TPR for each {N, K} and populate a cell of the performance matrix.

Results and Interpretations

The experiment was conducted (with t = 1%) for the above said values of K for two data sets – DARPA data set and the AUCK-II data set. The performance matrices for the two

data sets are indicated in Figures A1 and A2.

The following are the important observations:

• The performance matrix can be analyzed in two ways – Column wise analysis is done when N is fixed and a suitable K has to be arrived at, and row wise analysis to be done when the right N is chosen for fixed K. The former is more useful.

• The matrices show an important fact discussed above – for a given N , performance saturates after a particular value of K is reached, and addition of a few more bands does not improve the performance any more.

• The well tagged DARPA data set appears to have ideal properties – for even higher values of N , performance starts converging from small values of K. In essence, it means that the data set contains very few event occurrences for all N , which could be captured with fewer bands.

• From the results, it can be seen that when K is upper bound by N*5, the system performance peaks for almost all values of N and K in all three data sets.

K	N			
	50	100	150	200
5	0.83%	0.84%	0.9%	0.91%
10	0.84%	0.85%	0.9%	0.85%
15	89.58%	89.57%	0.86%	0.86%
20	89.58%	99.99%	0.87%	0.9%
30	99.99%	100%	100%	89.6%
40	99.99%	100%	100%	100%

Figure A.1: Performance Matrix for AUCK-II

K	N			
	50	100	150	200
5	68.14%	68.16%	68.16%	68.18%
10	100%	100%	68.17%	100%
15	100%	100%	100%	100%
20	100%	100%	100%	100%
30	100%	100%	100%	100%
40	100%	100%	100%	100%

Figure A.2: Performance Matrix for DARPA

Conclusion

Hence, it is hypothesized that K should be at least N*5 for the system to achieve good performance levels. The absence of constant values for K for any N is expected to create a few space overheads in hardware implementation (of detection), since N is expected to vary across multiple user sites, depending on their traffic profiles. This can be worked around by

implementing detection assuming a reasonably large value of N , and choosing to keep N 5 bands for model probabilities. This space can be dynamically handled for all values of N lesser than the chosen value. This may amount to wastage of reasonably small space, which can be easily handled by modern hardware.

Experiments on Error Percent 't'

The objective of this experiment is to determine precise values of t for different data sets. The previous experiment hypothesized the relation between N and K, and experiments on t preserve this relation. For the purpose of these experiments, N is assumed to be 100, and K, according to our hypothesis is chosen to be 20. With these values fixed, experiment is conducted by varying the value of t until a saturation point in performance, in terms of True Positives is reached. Since it has already been explained that increasing values of t will increase false positives, we are concerned more about the attack traffic and how efficient the system is with respect to classifying attack windows as attack, with a given t.

Experiment

The following procedure was used to conduct the experiment:

1. Training phase: Train with normal traffic.
2. Testing phase: Pass as input the attack traffic, and estimate the True Positives for every t.
3. Repeat the experiment for different values of t, and find out the value of t at which the number of True Positives converges to a maximum. This value is the actual value for the error percent t.

Results and Interpretations

The results of the experiment are graphically described in Figure A3 and A4. The value of t differs from site to site. The number of bands K determines the level of accuracy of modeling, and should be carefully chosen during system design. N and K are related to each other.

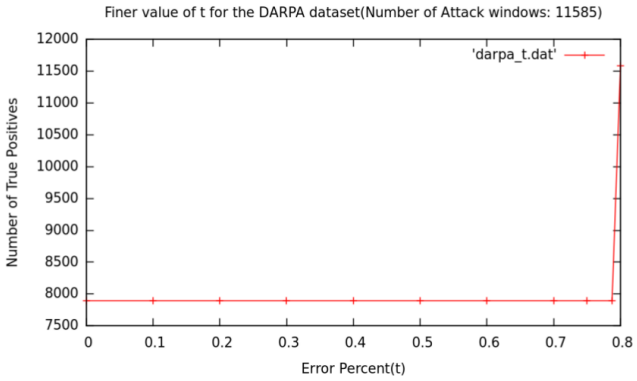


Figure A.3 Experiments to determine t (DARPA)

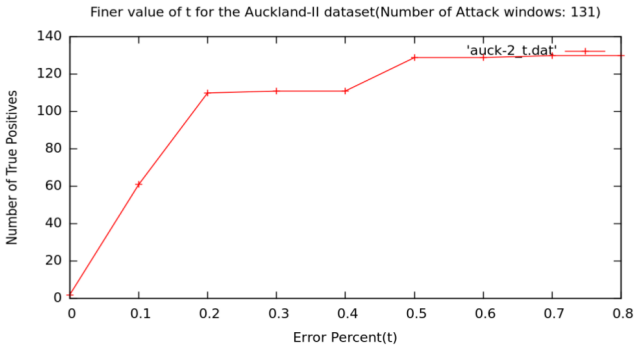


Figure A.4 Experiments to determine t (AUCK-II)

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