Anomaly Network Intrusion Detection Based on Improved Self Adaptive Bayesian Algorithm

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Abstract—Recently, research on intrusion detection in computer systems has received much attention to the computational intelligence society. Many intelligence learning algorithms applied to the huge volume of complex and dynamic dataset for the construction of efficient intrusion detection systems (IDSs). Despite of many advances that have been achieved in existing IDSs, there are still some difficulties, such as correct classification of large intrusion detection dataset, unbalanced detection accuracy in the high speed network traffic, and reduce false positives. This paper presents a new approach to the alert classification to reduce false positives in intrusion detection using improved self adaptive Bayesian algorithm (ISABA). The proposed approach applied to the security domain of anomaly based network intrusion detection, which correctly classifies different types of attacks of KDD99 benchmark dataset with high classification rates in short response time and reduce false positives using limited computational resources.

Index Terms—anomaly detection, network intrusion detection, alert classification, Bayesian algorithm, detection rate, false positives

I. INTRODUCTION

Network intrusion detection is the problem of detecting unauthorized use of computer systems over a network, such as the Internet. IDSs were introduced by James P. Anderson in 1980, an example of an audit trails would be a log of user access [1]. IDSs have become an integral part of today’s information security infrastructures. In order to detect intrusion activities, many machine learning (ML) algorithms, such as Neural Network [2], Support Vector Machine [3], Genetic Algorithm [4], Fuzzy Logic [5], and Data Mining [6], etc have been widely used to the huge volume of complex and dynamic dataset to detect known and unknown intrusions. It is very important for IDSs to generate rules to distinguish normal behaviors from abnormal behavior by observing dataset, which is the record of activities generated by the operating system that are logged to a file in chronologically sorted order. IDSs using ML algorithms aim to solve the problems of analyzing huge volumes of dataset and realizing performance optimization of detection rules. IDSs detect attacks on computer systems and signal an alert to the Computer Emergency Response Team (CERT). The network intrusion detection area is the arrival of new, previously unseen attacks, because hackers are very inventive and they use newer ways to disrupt the normal operation of servers and users. Anomaly detection detects new attacks which has not presented in the dataset by observing system activities and classifying it as either normal or anomalous. An important research challenge today is to develop adaptive IDSs to improve classification rates, and reduce false positives.

The Bayesian algorithm (BA) provides a probabilistic approach for classification [7], [8], which provides an optimal way to predict the class of an unknown example. It is widely used in many fields of data mining, image processing, bio-informatics, and information retrieval etc. It calculates conditional probabilities from a given dataset and used these conditional probabilities to find out the probabilities of belongingness to different classes. The unseen example is then categorized to that class, which assumes the maximum value. In this paper, based on a comprehensive analysis for the current research challenges we propose a new algorithm to address the problem of classification rates and false positives using improved self adaptive Bayesian Algorithm. This algorithm correctly classifies different types of attacks of KDD99 dataset with high detection accuracy in short response time, and also maximizes the detection rate (DR) and minimizes the false positives (FP). In our experiments proposed algorithm reduced the number of false positives by up to 90% with acceptable misclassification rates.

The remainder of this paper is organized as follows. Section II provides a review of IDSs and section III provides IDSs using machine learning algorithms. Section IV presents our proposed new algorithm. Experimental results are presented in section V. Finally, section VI makes some concluding remarks along with suggestions for further improvement.

II. REVIEW OF INTRUSION DETECTION SYSTEMS

A. History of IDSs

In 1980, the concept of IDSs began with Anderson’s seminal paper, introduced the notion that audit trails...
contained vital information that could be valuable in tracking misuse and understanding user behavior. His work was the start of host-based IDSs (HBIDSs). In 1986, Dr. Dorothy Denning published a model which revealed the necessary information for commercial IDSs development [9]. In 1988, multics intrusion detection and alerting system (MIDAS), an expert system using P-BEST and LISP was developed [10]. Haystack was also developed in this year using statistics to reduce audit trails [11]. In 1989, wisdom & sense (W&S) was a statistics-based anomaly detector developed, that created rules based on statistical analysis, and then used those rules for anomaly detection [12]. In 1990, Heberlein first introduced the idea of network IDSs, development of Network Security Monitor (NSM), and hybrid IDSs [13] and Lunt proposed SRI named intrusion detection expert system (IDES), a dual approach of a rule-based expert system and a statistical anomaly detection, which ran on Sun Workstations and could consider both user and network level data [14]. Also in the early 1990s the commercial development of IDSs were started and the Time-based inductive machine (TIM) did anomaly detection using inductive learning of sequential user patterns in Common LISP on a VAX 3500 computer [15]. In 1991, distributed IDSs (DIDS), an expert system created by the researchers of University of California [16], and the network anomaly detection and intrusion reporter (NADIR) a statistic based anomaly detector and also an expert system developed by Los Alamos National Laboratory’s Integrated Computing Network (ICN) [17].

In 1993, Lunt proposed the Next-generation Intrusion Detection Expert System by developing SRI followed IDES using artificial neural network [18]. The Lawrence Berkeley National Laboratory introduced rule language called Bro for packet analysis from libpcap dataset in 1998 [19]. The audit data analysis and mining IDSs used tcpdump to build profiles of rules for classifications in 2001 [20].

B. Types of IDSs

Intrusion is a set of actions that attempt to compromise the confidentiality, integrity or availability of computer resources. IDSs collect information from a variety of systems and analyze the information for signs of intrusions. In general, IDS categorize into five types, which are described below:

1) Network IDSs (NIDSs) responsible for detecting attacks related to the network [21], [22]. NIDSs investigate incoming and outgoing network traffic by connecting with network devices to find suspicious patterns. If a NIDS has no additional information about the protected host, the malicious attacker can easily avoid detection by taking advantage of different handling by overlapping IP/TCP fragments by IDS and a target host [23].

2) Host-based IDSs (HBIDSs) usually are located in servers to examine the internal interfaces [24]. HBIDSs can either use standard auditing tools [25], or specially instrumented operating system [26], or application platforms [27]. It detects intrusions by analyzing system calls, application logs, file-system modifications, and other host activities related to the machine.

3) Protocol-based IDSs (PIDSs) monitor the dynamic behavior and state of the protocol used the web server. PIDSs sit at the front end of a web server, monitoring and analyzing the HTTP protocol stream. It understands the HTTP protocol to protect web server by filtering IP address or port number.

4) Application protocol-based IDSs (APIDSs) monitor and analysis on a specific application protocol or protocols between a process, and group of servers that is used by the computer system. APIDSs can be sitting between a web server and the database management system that monitoring the SQL protocol specific to the business logic. Generally, APIDSs look for the correct use of the protocol.

5) Hybrid IDSs (HIDSs) combines two or more intrusion detection approaches. HIDS provide alert notification from both network and host-based intrusion detection devices.

C. Detection Models of IDSs

Detection rate (DR) is defined as the number of intrusion instances detected by the system divided by the total number of intrusion instances present in the dataset, and false positives (FP) is an alarm, which rose for something that is not really an attack. There are two types of detection models for IDSs, which are described below:

1) Misuse or signature-based IDSs are also known as pattern-based IDSs. It performs simple pattern matching to match a pattern corresponding to a known attack type in the database. DR of these IDSs is relatively low, because attacker will try to modify the basic attack signature in such a way that will not match the known signatures of that attack and it cannot detect a new attack for which a signature is not yet installed in the database.

2) Anomaly-based IDSs tries to identify new attacks by analyzing strange behavior from normal behaviors. It has a relatively high detection rate for new types of intrusion. The disadvantage is that in many cases there is no signal “normal profile” and anomaly-based systems tend to produce many false positives.

D. Functions of IDSs

IDSs are automated systems detecting and alarming of any situation where an intrusion has taken or is about to take place. According to the Common Intrusion Detection Framework (CIDF), generally IDSs consists of four components, like: sensors, analyzers, database, and response units. Most modern IDSs use multiple intrusion sensors, which obtain alerts from the large computational environment to maximize their trustworthiness. Analyzers use the input of the sensors, analyze the information gathered by these sensors, and return a synthesis or summary of the input. Today, machine learning algorithms have become an indispensable tool in the analyzers of IDSs. Database stores all alerts and support the analysis process. The response units carry out prescriptions controlled by the analyzers. The functions of IDSs are follows as [28]:

- Monitoring user’s activity.
A. Bayes Rule

The Bayes rule provides a way to calculate the probability of a hypothesis based on its prior probability \( P(h) \), the observed data \( P(D) \) plus any initial knowledge about the prior probabilities of the various hypotheses \( h \). Bayes rule is defined in equation “(1)”.

\[
Bayes Rule: \quad P(h|D) = \frac{P(D|h)P(h)}{P(D)} \tag{1}
\]

Here \( P(h|D) \) is the posterior probability, while \( P(h) \) is the prior probability associated with hypothesis \( h \). \( P(D) \) is the probability of the occurrence of data \( D \) and \( P(D|h) \) is the conditional probability. In many learning scenarios, the learner considers some set of candidate hypothesis, \( H \) and is interested in finding the most probable hypothesis \( h \in H \) given the data \( D \). Any such maximally probable hypothesis is called maximum posterior (MAP) hypothesis. The MAP hypothesis use Bayes rule to calculate the posterior probability of each candidate hypothesis. More exactly, \( h_{MAP} \) is a MAP hypothesis provided:

\[
h_{MAP} = \arg \max_h P(h|D) \tag{2}
\]

Finally, dropped the term \( P(D) \) because it is a constant dependent of \( h \). \( P(D|h) \) is also called likelihood of the data \( D \) given \( h \) any hypothesis that maximizes \( P(D|h) \) is called a Maximum Likelihood (ML) hypothesis, \( h_{ML} \):

\[
h_{ML} = \arg \max_h P(D|h) \tag{3}
\]

B. Naïve Bayesian Classifier

Naïve Bayesian (NB) classifier is a simple probabilistic classifier based on probability models that incorporate strong independence assumptions which often have no bearing in reality. The probability model can be derived using Bayes rule. Depending on the precise nature of the probability model, NB classifier can be trained very efficiently in a supervised learning. In many practical applications, parameter estimation for naïve Bayesian models uses the method of maximum likelihood. In spite of naïve design and apparently oversimplified assumptions, naïve Bayesian classifiers often work much better in many complex real-world situations.

The NB classifier is given as input a set of training examples each of which is described by attributes \( A_i \) through \( A_k \) and an associated class, \( C \). The objective is to classify an unseen example whose class value is unknown but values for attributes \( A_i \) through \( A_k \) are known and they are \( a_1, a_2, ..., a_k \) respectively. The optimal prediction of the unseen example is the class value \( c \) such that \( P(C=c|A_1=a_1, ..., A_k=a_k) \) is maximum. By Bayes rule this probability equals to

\[
\arg \max_{c \in C} \frac{P(A=a_1...A_k|C=c)P(C=c)}{P(A=a_1...A_k)} \tag{4}
\]

Where \( P(C=c) \) is the prior probability of class \( c \), \( P(A_1=a_1, ..., A_k=a_k) \) is the probability of occurrence of the description of a particular example, and \( P(A_1=a_1, ..., A_k=a_k|C=c) \) is the class conditional probability of the description of a particular example \( c \) of class \( C \). The prior probability of a class can be estimated from training data. The probability of occurrence of the description of particular examples is irrelevant for decision making since it is the same for each class value \( c \). Learning is therefore reduced to the problem of estimating the class conditional probability of all possible description of examples from training data. The class conditional probability can be written in expanded from as follows:

\[
P(A_1=a_1, ..., A_k=a_k|C=c) = P(A_1=a_1|A_2=a_2, ..., A_k=a_k \land C=c) \\
* P(A_2=a_2|A_3=a_3, ..., A_k=a_k \land C=c) \\
* P(A_3=a_3|A_4=a_4, ..., A_k=a_k \land C=c) \\
* P(A_4=a_4, ..., A_k=a_k \land C=c) \tag{5}
\]

In NB, it is assumed that outcome of attribute \( A_i \) is independent of the outcome of all other attributes \( A_j \) given \( c \). Thus class conditional probabilities become:

\[
P(A_1=a_1, ..., A_k=a_k|C=c) = \prod_{i=1}^{k} P(A_i=a_i \mid C=c) \tag{6}
\]

In Naïve Bayesian learning, the probability values of equation “(6)” are estimated from the given training data. These estimated values are then used to classify unknown examples.

C. Decision Tree Algorithms

The ID3 technique builds decision tree using information theory [29]. The basic strategy used by ID3 is to choose splitting attributes from a data set with the highest information gain. The amount of information associated with an attribute value is related to the probability of occurrence. The concept used to quantify
information is called entropy, which is used to measure the amount of randomness from a data set. When all data in a set belong to a single class, there is no uncertainty then the entropy is zero. The objective of decision tree classification is to iteratively partition the given data set into subsets where all elements in each final subset belong to the same class. The entropy calculation is shown in equation “(7)”. The value for entropy is between 0 and 1 and reaches a maximum when the probabilities are all the same. Given probabilities \( p_1, p_2, \ldots, p_s \) where \( \sum_{i=1}^{s} p_i = 1 \),

\[
\text{Entropy: } H(p_1, p_2, \ldots, p_s) = \sum_{i=1}^{s} p_i \log(1/p_i)
\]

(7)

Given a data set, \( D \), \( H(D) \) finds the amount of subset of data set. When that subset is split into \( s \) new subsets \( S = \{D_1, D_2, \ldots, D_s\} \), we can again look at the entropy of those subsets. A subset of data set is completely ordered if all examples in it are the same class. ID3 chooses the splitting attribute with the highest gain. The ID3 algorithm calculates the gain by the equation “(8)”.

\[
\text{Gain}(D, S) = H(D) - \sum_{i=1}^{s} \frac{n_i}{n} H(D_i)
\]

(8)

The C4.5 algorithm improves ID3 through GainRatio [30]. For splitting purpose, C4.5 uses the largest GainRatio that ensures a larger than average information gain.

\[
\text{GainRatio}(D, S) = \frac{\text{Gain}(D, S)}{H(D)}
\]

(9)

The C5.0 algorithm improves the performance of building trees using boosting, which is an approach to combining different classifiers. But boosting does not always help when the training data contains a lot of noise. When C5.0 performs a classification, each classifier is assigned a vote, voting is performed, and the example of data set is assigned to the class with the most number of votes. CART (classification and regression trees) is a process of generating a binary tree for decision making [31]. CART handles missing data and contains a pruning strategy. The SPRINT (Scalable Parallelizable Induction of Decision Trees) algorithm uses an impurity function called \( gini \) index to find the best split [32]. “Equation (10), defines the \( gini \) for a data set, \( D \).

\[
gini(D) = 1 - \sum p_i^2
\]

(10)

Where, \( p_i \) is the frequency of class \( C_i \) in \( D \). The goodness of a split of \( D \) into subsets \( D_1 \) and \( D_2 \) is defined by

\[
gini_{split}(D) = n_1/n \cdot gini(D_1) + n_2/n \cdot gini(D_2)
\]

(11)

The split with the best \( gini \) value is chosen. A number of research projects for optimal feature selection and classification have been done, which adopt hybrid strategy involving evolutionary algorithm and inductive decision tree learning [33], [34], [35], [36].

D. K-Nearest Neighbors

The K nearest neighbors (KNN) is a classification algorithm based on the use of distance measures [37]. It finds \( k \) examples in training data that are closest to the test example and assigns the most frequent label among these examples to the new example. When a classification is to be made for a new example, its distance to each attribute in the training data must be determined. Only the K closest examples in the training data are considered further. The new example is then placed in the class that contains the most examples from this set of K closest examples. KNN can be considered decision making technique as equivalent to Bayesian classifier in which the number of neighbors of each example is used as an estimate of the relative posterior probabilities of class membership in the neighborhood of a sample to be classified.

IV. IMPROVED SELF ADAPTIVE BAYESIAN ALGORITHM

A. Adaptive Bayesian Algorithm

Adaptive Bayesian algorithm creates a function from KDD99 benchmark intrusion detection training data [38], which first estimate the class conditional probabilities for each attribute value based on their frequencies over the weights with match of same class in the training data. In a given training data, \( D = \{A_1, A_2, \ldots, A_n\} \) of attributes, where each attribute \( A_i = \{A_{i1}, A_{i2}, \ldots, A_{ik}\} \) contains attribute values and a set of classes \( C = \{C_1, C_2, \ldots, C_m\} \), where each class \( C_j = \{C_{j1}, C_{j2}, \ldots, C_{jk}\} \) has some values. Each example in the training data contains weight, \( W = \{W_1, W_2, \ldots, W_k\} \). Initially, all the weights for each example of training data have equal unit value that set to \( W_i = 1.0 \). Then calculate the sum of weights for each class from the training data by counting how often each class occurs in the training data and the sum of weights for each attribute value with respect to same class in the training data. Next calculate the class conditional probabilities for each attribute value using equation “(12)” from the training data.

\[
P(A_i|C_j) = \frac{\sum W_i}{\sum W_j}
\]

(12)

Here \( P(A_i|C_j) \) is the class conditional probability, \( W_d \) is the sum of weights for each attribute value, and \( W_j \) is the sum of weights for each class. After calculating the class conditional probabilities for each attribute value from the training data, the algorithm classify the each test example using equation “(13)”.

\[
\text{Target Class} = \prod_{C_j} P(A_i|C_j)
\]

(13)

If any test example is misclassified, the algorithm updates the weights of training data. The algorithm compare each of test examples with every training example and compute the similarity between them, and then weights of training data are increased by a fixed
small value multiplied by the corresponding similarity measure.

\[ W_i = W_i + (S \times 0.01); \]  

(14)

Here \( S \) is the similarity between test and training examples. If the test example is correctly classified, then the weights of training data will remain unchanged. After weights adjustment, the class conditional probabilities for attribute values are recalculated from the modified weights in training data. If the new set of probabilities correctly classifies all the test examples, the algorithm terminates. Otherwise, the iteration continues until all the test examples are correctly classified or the target accuracy is achieved. At this stage the algorithm terminates, the class conditional probabilities are preserved for future classification of seen or unseen examples.

B. Improved Self Adaptive Bayesian Algorithm

Improved self adaptive Bayesian algorithm (ISABA) is the modification of adaptive Bayesian algorithm. Given a training data ISABA initializes the weights of each example \( W_i \) set to 1.0 and estimates the prior probability \( P(C_j) \) for each class by summing the weights how often each class occurs in the training data. For each attribute in training data, \( A_i \) the number of occurrences of each attribute value \( A_{ij} \) can be counted by summing the weights to determine the probability \( P(A_{ij}) \). Similarly, the probability \( P(A_{ij} \mid C_j) \) can be estimate by summing the weights how often each attribute value occurs in the class in the training data. An example in the training data may have many different attributes \( A = \{A_1, A_2, \ldots, A_n\} \), and each attribute have many values \( A_i = \{A_{i1}, A_{i2}, \ldots, A_{ik}\} \). The conditional probability \( P(A_{ij} \mid C_j) \) estimate for all values of attributes. Then the algorithm uses these conditional probabilities to classify all the training examples. 

When classifying a training example, the conditional and prior probabilities generated from the training data are used to make the prediction. This is done by multiplying the probabilities of the different attribute values from the example. Suppose the training example \( e_i \) has \( p \) independent attribute values \( \{A_{i1}, A_{i2}, \ldots, A_{ip}\} \), the algorithm has \( P(A_{ij} \mid C_j) \) for each class \( C_j \) and attribute \( A_{ij} \), and then estimate probability \( P(e_i \mid C_j) \) by using equation ‘(15)’.

\[ P(e_i \mid C_j) = P(C_j) \prod_{k=1}^{p} P(A_{ij} \mid C_j) \]  

(15)

To calculate the probability \( P(e_i) \), the algorithm estimate the likelihood that \( e_i \) is in each class. The probability that \( e_i \) is in a class is the product of the conditional probabilities for each attribute values. The posterior probability \( P(C_j \mid e_i) \) is then found for each class. The class with the highest probability is the one chosen for the example in training data. Now the algorithm updates the weights for each example in the training data with the highest value of posterior probability \( P(C_j \mid e_i) \) for that example and also changes the class value associate with highest posterior probability. If any example in the training data is misclassified then the algorithm again calculates the prior probability \( P(C_j) \) and conditional probability \( P(A_{ij} \mid C_j) \) from the training examples using the updated weights, and again classify the training examples and updates the weights of training examples. This iteration will continue until all the training examples are correctly classified or the target accuracy is achieved.

After classifying the training examples, the algorithm classify the test examples using the conditional probabilities \( P(A_{ij} \mid C_j) \). If any test example is misclassified, the algorithm again updates the weights of training examples. The algorithm compares each of test example with every training examples and compute the similarity between them (out of four attributes two attribute values are same then similarity becomes 0.5 or one attribute value is same then similarity is 0.25 and so on), and then weights of training examples are increased by a fixed small value multiplied by the corresponding similarity measure. If the test examples are correctly classified, then the weights of training examples will remain unchanged. After weights adjustment, the conditional probabilities \( P(A_{ij} \mid C_j) \) for attribute values are recalculated from the modified weights of training examples. If the new set of probabilities correctly classifies all the test examples, the algorithm stores the conditional probabilities and builds a decision tree by information gain using last updated weights. Otherwise, the iteration continues until all the test examples are correctly classified or the target accuracy is achieved. At this stage the algorithm correctly classifies all the test examples, the conditional probabilities \( P(A_{ij} \mid C_j) \) are preserved for future classification of seen or unseen intrusions, and builds a decision tree by information gain using the last updated weights of training examples, which is also used for classification of seen or unseen intrusions. The main procedure of ISABA algorithm is described as follows.

**Algorithm ISABA**

Input: training data \( D \), testing data
Output: intrusion detection model

Procedure:

1. Initialize all the weights in \( D, W_i = 1.0 \).
2. Calculate the prior probabilities \( P(C_j) \) for each class \( C_j \) from \( D \).

\[ P(C_j) = \frac{\sum_{i=1}^{n} W_i}{\sum_{i=1}^{n} W_i} \]  

3. Calculate the probabilities \( P(A_{ij} \mid C_j) \) for each attribute value \( A_{ij} \) from \( D \).

\[ P(A_{ij}) = \frac{\sum_{j=1}^{c} W_j}{\sum_{j=1}^{c} W_j} \]  

4. Calculate the conditional probabilities \( P(A_{ij} \mid C_j) \) for each attribute values from \( D \).
5. Classify each example in \( D \).
\[
P(e_i \mid C_j) = P(C_j) \prod P(A_{ij} \mid C_j)
\]
6. Initialize all the weights in \( D \) with Maximum Likelihood (ML) of posterior probability \( P(C_j \mid e_i) \) and change the class value associated with highest posterior probability.
\[
W_i = P_{\text{ML}}(C_j | e_i)
\]
\[
C_j = C_i \rightarrow P_{\text{ML}}(C_j | e_i)
\]
7. If any example in \( D \) is misclassified, then go to step 2, else go to step 8.
8. Classify all test examples with the conditional probabilities \( P(A_{ij} \mid C_j) \).
9. If any test example is misclassified then update the weights of \( D \) using similarity \( S \).
\[
W_i = W_i + (S + 0.01)
\]
10. If weight update, then recalculate the probabilities \( P(A_{ij}) \) and \( P(A_{ij} \mid C_j) \) using updated weights of \( D \) and go to step 8.
11. If all test examples are correctly classified then the algorithm stores conditional probabilities for future classification of seen or unseen intrusions.
12. The algorithm builds decision tree by information gain using final updated weights of training examples.

V. EXPERIMENTAL RESULTS

A. Experimental Data

The KDD99 dataset is a common benchmark for evaluation of intrusion detection techniques [39]. In the 1998 DARPA intrusion detection evaluation program, a simulated environment was set up to acquire raw TCP/IP dump data for a local-area network (LAN) by the MIT Lincoln Lab to compare the performance of various intrusion detection methods. The DARPA98 was operated like a real environment, but being blasted with multiple intrusion attacks and received much attention in the research community of adaptive intrusion detection. In 1999, based on the DARPA98 data the Third International Knowledge Discovery and Data Mining Tools Competition established the KDD99 benchmark dataset for intrusion detection based on data mining. In the KDD99 data set, each data example represents attribute values of a class in the network data flow, and each class is labeled either as normal or as an attack with exactly one specific attack type. The KDD99 data records are all labeled with one of the following five types:

1) Normal connections are generated by simulated daily user behavior such as downloading files, visiting web pages, etc.
2) Denial of Service (DoS) attack causes the computing power or memory of a victim machine too busy or too full to handle legitimate requests. DoS attacks are classified based on the services that an attacker renders unavailable to legitimate users. Example of DoS attacks are Apache2, Land, Mail bomb, Back, etc.
3) User to Root (U2R) is a class of attacks that an intruder/hacker begins with the access of a normal user account and then becomes a super-user by exploiting various vulnerabilities of the system. Most common exploits of U2R attacks are regular buffer overflows, Loadmodule, Fdformat, and Ffbconfig.
4) Remote to User (R2L) is a class of attacks that a remote user gains access of a local account by sending packets to a machine over a network communication, which include Sendmail, and Xlock.
5) Probing (Probe) is an attack scans a network to gather information or find known vulnerabilities. An intruder with a map of machines and services that are available on a network can use the information to look for exploits.

B. Experimental Analysis

Correct classification of known and unknown intrusions is one of the central problems for network-based intrusion detection. Many supervised and unsupervised learning algorithms already applied to classifying intrusions but their performance were not very satisfactory due to the challenging problem of detection novel attacks with low false alarms. In order to evaluate the performance of improved self-adaptive Bayesian algorithm (ISABA) for intrusion detection, we performed 5-class classification using KDD99 benchmark dataset. The training and testing data are taken randomly from the KDD99 dataset with different ratios of positive versus negative instance. The training data are used to train the algorithms, and the test data are used to evaluate the performance of the algorithms. Table I shows the number of examples in 10% training data and 10% testing data of KDD99 dataset. There are some new attack examples in testing data, which is no present in the training dataset.

<table>
<thead>
<tr>
<th>Attack Types</th>
<th>Training Examples</th>
<th>Testing Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>97277</td>
<td>60592</td>
</tr>
<tr>
<td>Probing</td>
<td>4107</td>
<td>4166</td>
</tr>
<tr>
<td>Denial of Service</td>
<td>391458</td>
<td>237594</td>
</tr>
<tr>
<td>User to Root</td>
<td>52</td>
<td>70</td>
</tr>
<tr>
<td>Remote to User</td>
<td>1126</td>
<td>8606</td>
</tr>
<tr>
<td>Total Examples</td>
<td>494020</td>
<td>311028</td>
</tr>
</tbody>
</table>

In the experiments, first we performed the classification on KDD99 testing data using naive Bayesian classifier (NB), adaptive Bayesian algorithm (ABA), and improved self-adaptive Bayesian algorithm (ISABA) and compare their results shown in Table II. It is clear that the proposed new algorithm is approximately 2 times faster in training and testing than conventional algorithms.
The performance comparison between NB and ISABA on KDD99 (using 41 attributes) testing data is listed in Table III, which shows that the ISABA performs balanced and high classification rates on 5 attack classes of KDD99 data and minimize the false positives.

We tested our proposed algorithm using the reduced dataset of 12 attributes and 17 attributes in KDD99 dataset, which increase the classification rate for intrusion classes that are summarized in Table IV.

We also compare the detection performance among Support Vector Machines (SVM), Neural Network (NN), Genetic Algorithm (GA), Naïve Bayesian Classifier (NB), and improved self adaptive Bayesian algorithm (ISABA) on KDD99 dataset [40],[41],[42]. In total, 40 attributes of KDD99 dataset have been used. Each connection can be categorized into five main classes (one normal class and four main intrusion classes: probe, DoS, U2R, and R2L). The experimental setting uses 494020 data samples for training and 311028 data samples for testing. The comparative results are summarized in Table V.

### Table II
**Training and Testing Time Comparison**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Training Time (s)</th>
<th>Testing Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve Bayesian Classifier</td>
<td>42.9</td>
<td>18.4</td>
</tr>
<tr>
<td>Adaptive Bayesian Algorithm</td>
<td>24.6</td>
<td>9.6</td>
</tr>
<tr>
<td>Improved Self Adaptive Bayesian Algorithm</td>
<td>28.4</td>
<td>7.5</td>
</tr>
</tbody>
</table>

### Table III
**Performance Comparison between NB and ISABA**

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>Probe</th>
<th>DoS</th>
<th>U2R</th>
<th>R2L</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve Bayesian Classifier (DR %)</td>
<td>99.25</td>
<td>99.13</td>
<td>99.69</td>
<td>64</td>
<td>99.11</td>
</tr>
<tr>
<td>Naïve Bayesian Classifier (FP %)</td>
<td>0.08</td>
<td>0.45</td>
<td>0.04</td>
<td>0.14</td>
<td>8.02</td>
</tr>
<tr>
<td>Improved Self Adaptive Bayesian Algorithm (DR %)</td>
<td>99.62</td>
<td>99.22</td>
<td>99.49</td>
<td>99.17</td>
<td>99.15</td>
</tr>
<tr>
<td>Improved Self Adaptive Bayesian Algorithm (FP %)</td>
<td>0.05</td>
<td>0.36</td>
<td>0.03</td>
<td>0.10</td>
<td>6.91</td>
</tr>
</tbody>
</table>

### Table IV
**Performance of ISABA Using Reduced Datasets**

<table>
<thead>
<tr>
<th></th>
<th>12 Attributes</th>
<th>17 Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>99.97</td>
<td>99.96</td>
</tr>
<tr>
<td>Probe</td>
<td>99.91</td>
<td>99.95</td>
</tr>
<tr>
<td>DoS</td>
<td>99.99</td>
<td>99.98</td>
</tr>
<tr>
<td>U2R</td>
<td>99.36</td>
<td>99.46</td>
</tr>
<tr>
<td>R2L</td>
<td>99.53</td>
<td>99.69</td>
</tr>
</tbody>
</table>

### Table V
**Comparison of Several Algorithms**

<table>
<thead>
<tr>
<th></th>
<th>SVM</th>
<th>NN</th>
<th>GA</th>
<th>NB</th>
<th>ISABA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>99.4</td>
<td>99.6</td>
<td>99.3</td>
<td>99.55</td>
<td>99.82</td>
</tr>
<tr>
<td>Probe</td>
<td>89.2</td>
<td>92.7</td>
<td>98.46</td>
<td>99.43</td>
<td>99.72</td>
</tr>
<tr>
<td>DoS</td>
<td>94.7</td>
<td>97.5</td>
<td>99.57</td>
<td>99.69</td>
<td>99.49</td>
</tr>
<tr>
<td>U2R</td>
<td>71.4</td>
<td>48</td>
<td>99.22</td>
<td>64</td>
<td>99.47</td>
</tr>
<tr>
<td>R2L</td>
<td>87.2</td>
<td>98</td>
<td>98.54</td>
<td>99.11</td>
<td>99.35</td>
</tr>
</tbody>
</table>

We also compare the detection performance among Support Vector Machines (SVM), Neural Network (NN), Genetic Algorithm (GA), Naïve Bayesian Classifier (NB), and improved self adaptive Bayesian algorithm (ISABA) on KDD99 dataset [40],[41],[42]. In total, 40 attributes of KDD99 dataset have been used. Each connection can be categorized into five main classes (one normal class and four main intrusion classes: probe, DoS, U2R, and R2L). The experimental setting uses 494020 data samples for training and 311028 data samples for testing. The comparative results are summarized in Table V.

### Table V
**Comparison of Several Algorithms**

<table>
<thead>
<tr>
<th></th>
<th>SVM</th>
<th>NN</th>
<th>GA</th>
<th>NB</th>
<th>ISABA</th>
</tr>
</thead>
<tbody>
<tr>
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</table>

The ROC (relative operating characteristic) curve shows the relationship between detection rate and false positives on 10% KDD99 testing data in figure 1.

**VI. CONCLUSION AND FUTURE WORKS**

The main advantage of this proposed algorithm is to generate a minimal rule set for network intrusion detection, which can detect network intrusions based on previous activities. Proposed algorithm analyzes the large volume of network data and considers the complex properties of attack behaviors to improve the performance of detection speed and detection accuracy. This paper presents a new intrusion detection algorithm based on intelligent machine learning algorithms. In this paper we have concentrated on the development of the performance of naïve Bayesian classifier, which adjusts the weights of training examples until either all the test examples are correctly classified or the target accuracy on test examples is achieved. The experimental results marked that this algorithm minimized false positives, as well as maximize balance detection (classification rates) on the 5 classes of KDD99 data. The future research issues will be applying domain knowledge of security to improve the detection accuracy, and visualizing the procedure of intrusion detection in real world problem domains.

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**REFERENCES**


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