

Analysis of Intrusion Detection Technique In Data Mining: A Survey

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Abstract:- Cyber terrorism has recently been said to be the biggest threat to our modern society. Every day a new cyberscare story makes the headlines. The national government recognizes the importance of cyber security, as several officials have made clear in the past few years "Cyber security is among the most serious economic and national security challenges we will face in the 21st Century, we face a long-term challenge in cyberspace from foreign intelligence agencies and militaries, criminals, and others, and, this struggle will wreak serious damage on the economic health and national security. For the prevention and detection of cyber terrorism used intrusion detection system, intrusion detection system detects illegal behavior of network over data. In current research trend performance of intrusion detection system is important issue. Now various authors' used machine learning and feature optimization technique for intrusion detection system. Machine learning technique is collection of all learning algorithm such as classification, clustering and regression. For the improvement of machine learning technique used feature optimization technique. In this paper presents review of intrusion detection technique using machine learning and feature optimization process.

Key Terms:- IDS, Machine Learning, Feature Optimization, KDDCUP, Traffics features, PCA.

1. INTRODUCTION

The advancement of information communication network contributes the improvement of the quality of daily life of people, and now considered as fundamental social and economic infrastructure. However, the increase of incidents and threats against this infrastructure has turned out to be a serious problem. These days it is very significant to maintain a high level security to ensure protected and trust information message among different groups. But integrity of data over internet and any other network is always under threat of intrusions and misuses. So Intrusion Detection Systems (IDS) have become crucial components in computer and network security [6]. Improvement of intrusion detection technique in major concern of financial sector and social networking site use of common user. The computer security community has developed a variety of intrusion detection systems to prevent attacks on computer systems. Feature optimization and feature reduction is major challenges in current researcher trend in intrusion detection technique. Irrelevant and redundant attributes of intrusion detection dataset may lead to complex intrusion detection model as well as

reduce detection accuracy. The network based intrusion detection is called as mysterious attacks and this attack is analyzed on the basis of normal attack scenario [20]. Despite all the applied mechanism for intrusion detection system not provide the complete secured data. Therefore, intrusion detection is becoming an increasingly important technique that monitors network traffic and identifies network intrusions attacks to computer systems. A number of machine learning based approaches have been used for detecting abnormal threats. Machine learning refers to a group of techniques that develop the easiness for ambiguity, improbability, incomplete fact, and estimate to achieve toughness and low solution price. The principle constituents of machine learning are Fuzzy Logic (FL) [18, 15], Artificial Neural Networks (ANNs), Probabilistic Reasoning (PR), and Genetic Algorithms (GAs). The Genetic Algorithm is used to detect the intrusions in networks [3, 19]. It considers both temporal and spatial information of network connections during the encoding of the problem using Genetic Algorithm. Data mining is an efficient method for intrusion detection, which can dig out the unknown knowledge and rules from a large number of network data or audit data from host. The Genetic Algorithm is more helpful for identification of network anomalous behaviors. The Rough Set Neural Network Algorithm is used to reduce a number of computer resources required to detect an attack. The KDDCup'99 dataset is used to test the data and gives the better and robust result. The various feature reduction techniques such as Independent Component Analysis, Linear Discriminate Analysis and Principal Component Analysis used to reduce the computational intensity. KDD cup 99 dataset is used to reduce computation time and improves the accuracy of the systems. Section-I gives the introduction of the intrusion detection. Section-II gives the traffic feature of intrusion detection system. Problem formulations in intrusion detection have been reviewed in section-III. Section IV discusses comparative result evaluation. Finally, section-V is the conclusion and future scope.

II.TRAFFIC FEATURE OF NETWORK

The generation of network traffic is very large amount, processing of this traffic data is very difficult for firewall, intrusion detection system and other security analysis of tools. The generated traffic is not formatted, due to this



reason the classification of traffic categories is very difficult. For the analysis of traffic data used KDD mining tools and converted into connection and sequence data [12]. These sequence and connection data have 42 features on different categories such as basic feature data, content feature, time based feature and host traffic based feature.

- 1. Basic Features: the basic feature of these categories gets information from packet header without information of payload. The content of these categories is 1 to 8.
- 2. Content Features: In this group new TCP packets analyzed with help of area information. An example of this category is number of "hot" indicator.
- 3. Time-based Traffic Features: for gathering these types of features a window of 2 second interval is defined. In this interval, some properties of packets are measured. For example number of connections to the same service as the current connection in the past two seconds.
- 4. Host-based Traffic Features: In this category instead of a time based window, a number of connections are used for building the window. This category is designed so that attacks longer than 2 second can be detected.

The processing of feature and description of feature discuss in table 1, 2 and 3 according to their description and data type.

Table 1: Basic features of individual TCP connections

Feature name	Description	Type
hot	number of	continuou
	``hot"	S
	indicators	
num_failed_logins	number of	continuou
	failed login	S
	attempts	
logged_in	1 if	discrete
	successfully	
	logged in; 0	
	otherwise	
num_compromised	number of	continuou
	``compromised'	S
	' conditions	
root_shell	1 if root shell is	discrete
	obtained; 0	
	otherwise	
su_attempted	1 if ``su root"	discrete
	command	
	attempted; 0	
	otherwise	
num_root	number of	continuou
	``root"	s
	accesses	
num_file_creations	number of file	continuou
	creation	s
	operations	
num_shells	number of shell	continuou
_	prompts	S
num_access_files	number of	continuou

	operations on	S
	access control	
	files	
num_outbound_cmd	number of	continuou
s	outbound	S
	commands in	
	an ftp session	
is_hot_login	1 if the login	discrete
	belongs to the	
	"hot" list; 0	
	otherwise	
is_guest_login	1 if the login is	discrete
	a ``guest"login;	
	0 otherwise	

Table 2: Content features within a connection suggested by domain knowledge.

Feature	Description	Туре
name	Description	Type
count	number of	continuous
Count	connections to	Continuous
	the same host as	
	the current	
	connection in	
	the past two	
	seconds	
serror_rate	% of	continuous
	connections that	
	have "SYN"	
	errors	
rerror rate	% of	continuous
_	connections that	
	have "REJ"	
	errors	
same srv rate	% of	continuous
	connections to	
	the same	
	service	
diff_srv_rate	% of	continuous
	connections to	
	different	
	services	
srv_count	number of	continuous
	connections to	
	the same service	
	as the current	
	connection in	
	the past two	
	seconds	
srv_serror_rat	% of	continuous
e	connections that	
	have "SYN"	
	errors	
srv_rerror_rat	% of	continuous
e	connections that	
	have ``REJ"	
1100 1	errors	-*
srv_diff_host_	% of	continuous
rate	connections to	



Table 3: Traffic features computed using a two-second time window.

Feature name	Description	Type
count	number of connections to the same host as the current connection in the past two seconds	continuous
serror_rate	% of connections that have ``SYN" errors	continuous
rerror_rate	% of connections that have ``REJ" errors	continuous
same_srv_rate	% of connections to the same service	Continuou s
diff_srv_rate	% of connections to different services	Continuou 5
srv_count	number of connections to the same service as the current connection in the past two seconds	Continuou s
srv_serror_rate	% of connections that have ``SYN" errors	Continuou 5
srv_rerror_rate	% of connections that have ``REJ" errors	Continuou 5
srv_diff_host_ rate	% of connections to different hosts	continuous

Feature selection and feature reduction is an important data processing step prior to perform of intrusion detection technique [17]. Feature optimization and feature reduction process used some heuristic function such as genetic algorithm, particle of swarm optimization and neural network. In the all categories of feature some features play ideal role in connection stream in case of normal connection and abnormal connection. if reduces these feature improve the performance of intrusion detection technique.

III PROBLEM FORMULATION

The environment in which the feature extraction and feature reduction is done it is crucial section for intrusion detection. This means that the network traffic contains user confidential information. In general, only the header fields of the packets can be checked but not the user data in the payload. Scalability is an issue with IDS. Because of the huge amount of data flowing through the mobile operator's network, it is not an easy task to find out the right information needed for IDS. The problem is to find an answer to the question: "What features need to be taken into account when calculating or analyzing whether the activity is malicious or not?"Based on prior research on IDS it is clear that either one of the techniques alone cannot detect everything but the combination of the both is the most promising approach. For example misuse detection can be used to filter known threats from the traffic to make it easier for the anomaly detection system to focus on the unknown. Even though IDS have been researched over 20 years, we still do not have an answer to

the question of what features should be monitored. So far different kinds of methods and algorithms have been developed for anomaly detection but the focus has been on making them more efficient. Almost all of them are lacking the same information; what features are important for IDS, especially in telecommunications networks? For some reason information on the used features is not easily found from IDS research publications. No matter what the reason is the result is the same; every researcher has to figure out by themselves which features should be used for the monitoring.

- 1. The pre-processing of KDDCUP99 takes more time.
- 2. The rate of false alarm generation is high.
- Some data mining classifier are ambiguous situation for selection of base classifier
- 4. Entropy based intrusion detection system suffered by high false rate
- 5. The detection of dynamic feature evaluation.

IV COMPARATIVE STUDY OF DETECTION TECHNIQUE

In this section discuss the comparative study of intrusion detection based on machine learning and feature optimization. The study used method detection rate and finally demerits of method.

Table 4: Comparative study of different intrusion detection techniques.

Sr No				
1. Fuzzy Genetic algorithm [1] 2. Neural network classifier [2] 3. Learning Lamstar Neural Network [4] 4. Decision tree classifier with feature based GA techniques [5] 5. Feature reduction with KNN and Bayes classifier [7] 6. Random forest classifier with classifier classifier genetic detection rate detection nate approxim ate pefficiency genetic detection number of data attribute Efficiency can be improve further with using feature reduction SOM which shows poor result for PROBE class. Decision tree not included the forest tree. Sometimes Computation cost may not be supported Not useful for Real time adaptive ID System				Demerits
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with System System	l		less time	
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		SMOTE		



7.	Genetic Approach [9]	Improved model for misuse detection system Detection	Method support only some feature in KDDCUP Results not
	mining and neural network approach [10]	rate for RBF is 98.50%	compared with any PCA Approach
9.	Attribute selection and classificatio n method [11]	Gives Accuracy is 99.00%	Model does not apply with Real world
10.	Unsupervis ed Neural network [13]	Accuracy 97.00% with ART and 95.00% SOM nets	ART-2 offered a little lower detection rate performance than ART-1
11.	Genetic Algorithm [14]	Accuracy for training data set is 97.25% and testing set is 95.00%	For the Large training rate of datasets, it is neither efficient nor feasible
12.	Fuzzy Based Divide Conquer Algorithm [16]	Classificat ion rate is 99.96%	Works only for selected features
13.	Feature selection and Ensemble method [16]	Accuracy for Probe is 100% and for R2L is 99.97%	U2R gives not better result, it's suffered
14	FNN-SVM [21]	Average accuracy performan ce is 97%	Very complex model used more time for execution

V CONCLUSION AND FUTURE SCOPE

In this paper study of intrusion detection technique using machine learning and feature optimization technique. In the study we seen that features of network data is very complex due to mixed categories. For the classification task feature selection and feature optimization is important technique. For the optimization of feature and reduction of feature used neural network technique, genetic algorithm and particle of swarm optimization technique. We also saw that merging a different classification technique also improved the detection of intrusion detection. All the method used in this survey gives average 98% detection rate with false alarm generation. In future increase the detection rate approximate 100 % and reduces the false alarm generation.

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