

Machine learning Solution for Detecting network Attacks

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ABSTRACT

Developing Intrusion Detection System (IDS) by setting the real working environment to explore all the possibilities of attacks is expensive. Software to detect network intrusions protects a computer network from unauthorized users, including perhaps insiders. The intrusion detector learning task is to build a predictive model (i.e. a classifier) capable of distinguishing between "bad" connections, called intrusions or attacks, and "good" normal connections. To prevent this problem in network sectors have to predict whether the connection is attacked

or not from KDD Cup 99 dataset using machine learning techniques. The aim is to investigate machine learning based techniques for better packet connection transfers forecasting by prediction results in best accuracy from ensemble learning voting classifier technique. To propose a machine learning-based method

to accurately predict the DOS, R2L, U2R, Probe and other attacks by prediction results in the form of best accuracy from comparing supervised classification machine learning algorithms with voting classifiers. Additionally, to compare and discuss the performance of various machine learning algorithms from the given dataset with the valuation classification report, identify the confusion matrix and to categorizing data from priority and the result shows that the effectiveness of the proposed machine learning algorithm technique can be compared with best accuracy with precision, Recall and F1 Score.

Key words: Developing Intrusion Detection System, DOS, Network attacks, machine learning algorithm

I. INTRODUCTION

This analysis aims to observe which features are most helpful in predicting the network attacks of DOS, R2L, U2R, Probe and combination of attacks or not and to see the general trends that may help us in model selection and hyper parameter selection. To achieve used machine learning classification methods to fit a function that can predict the discrete class of new input.

Lately, an internet network company in Japan has been facing huge losses due to malicious server attacks. They've encountered breach in data security, reduced data transfer speed and intermittent breakdowns in user-user & user-network connections. When asked, a company official said, "there's a significant dip in the number of active users on our network". The company is looking for some predictive analytics solution to help them understand, detect and counter the attacks and make their network connection secure. Think of a connection as a sequence of TCP packets starting and ending at some well-defined times, between which data flows to and from a source IP address to a target IP address under some well-defined protocol. In total, there are 3 major types of attacks to which their network

is vulnerable to. But, 3 of them cause the maximum damage. In this challenge, you are given an anonymised sample dataset of server connections. The type of attack(s) like Dos, R2L, U2R, Probe have to be predicted.

In the existing system, development of connected devices and their daily use is presently at the origin of the omnipresence of Wi-Fi wireless networks. However, these Wi-Fi networks are often vulnerable, and can be used by malicious people to disturb services, intercept sensitive data, or to gain access to the system. In railways, trains are now equipped with wireless communication systems for operational purposes or for passenger services. In both cases, defense strategies have to be developed to prevent the misuses of the networks. The first objective of this study is to propose a monitoring solution, which is independent of the communication networks, to detect the occurrence of attacks.

Our proposed system is not meant to be providing a final conclusion on there are

ons leading to network sector as it doesn't involve using any inferential statistic techniques/machine learning algorithms. Machine learning supervised

classification algorithms will be used to give the network connection dataset and extract patterns, which would help in predicting the likelihood of a patient affected or not, thereby helping the attack avoid making better decisions in the future. Multiple datasets from different sources would be combined to form a generalized dataset, and then different machine learning algorithms would be applied to extract patterns and to obtain results with maximum accuracy.

II. LITERATURE SURVEY

In an early warning system, accurate prediction of DoS attacks is the prime aim in the network offense and defense task. Detection based on abnormality is effective to detect DoS attacks. A various studies focused on DoS attacks from different respects [1]. Socio-technical attack is an organized approach which is defined by the interaction among people through maltreatment of technology with some of the malicious intent to attack the social structure based on trust and faith. [2][3]. Intrusion detection systems (IDS) are used to detect the occurrence of malicious activities against IT system. Alerts relations are differentiated from duplication relations to same attack scenario relation [4]. The prediction results reflect the security situation of the target network in the future, and security administrators can take corresponding measures to enhance network security according to the results. Many models have been proposed for performing evaluation of network security [5]. Meanwhile, with the Bayesian method, the calculation of the output probability corresponding to each sub-model is deduced and then the distribution of the amount of DoS attacks in some range in future is obtained [6][7].

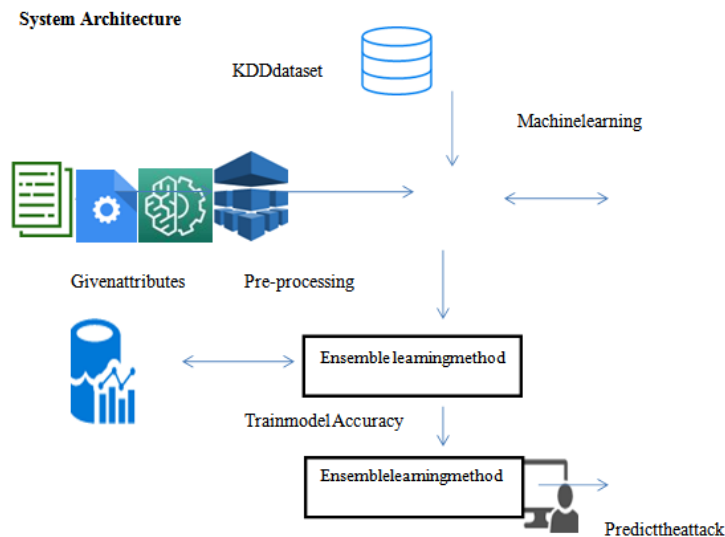
This paper attempted to cover the state-of-the-art studies for adversarial examples in the DL domain. Compared with recent work on adversarial examples, we analyzed and discussed the current challenges and potential solutions in adversarial examples [8]. This paper has investigated the distributed secure control of multi-agent systems under DoS attacks. We focus on the investigation of a jointly adverse impact of distributed DoS attacks from multiple adversaries [9]. For the event-triggered case, two effective dynamical event conditions have been designed and implemented in a fully distributed way, and both of them have excluded Zeno behavior. Finally, a simulation example has been provided to verify the

effectiveness of theoretical analysis [10].

III. METHODOLOGY

As networked systems become more and more pervasive and businesses continue to move more and more of their sensitive data online, the number and sophistication of cyber-attacks and network security breaches has risen dramatically. In earlier years, there are two kinds of big companies in the United States. There are those who've been hacked... and those who don't yet know they've been hacked." In order to secure their infrastructure and protect sensitive assets, organizations are increasingly relying on network intrusion detection systems (NIDS) to automatically monitor their network traffic and report suspicious or anomalous behavior. Historically, most NIDS operate in one of two styles: misuse detection and anomaly detection. Misuse detection searches for precise signatures of known malicious behavior, while anomaly detection tries to build a model for what constitutes "normal" network traffic patterns and then flag deviations from those patterns. For all the same reasons that signature-based antivirus software is becoming obsolete (the ease of spoofing signatures and the increasing diversity and sophistication of new attacks), misuse-detection is struggling to remain relevant in today's threat landscape. Anomaly-based intrusion detection offers the enticing prospect of being able to detect novel attacks even before they've been studied and characterized by security analysts, as well as being able to detect variations on existing attack methods. In our project we focus on classifying anomalies using both supervised and unsupervised learning techniques.

In order to create data for the IDS, it is necessary to set the real working environment to explore all the possibilities of attacks, which is expensive. Data analysis phases systematically identifies the patterns in the gathered information, and narrates them to the defined issue. It is a process of examining, transforming and modeling of data and deciding how to organize, classify, interrelate, compare and display it. Data quality focuses on the correctness and reliability of information gathered and utilized in an evaluation. Data quantity deals with the quantity of information gathered for the evaluation. This task requires various ground truth databases in its region and the experimentation would be completed effectively if the quality and features of data for the specific region are good.



DATASET

The KDD Cup99 data set stems from data gathered at MIT Lincoln Laboratory under sponsorship of the Defense Advanced Research Projects Agency (DARPA) to evaluate Intrusion Detection Systems (IDSs) in 1998 and 1999. These two data sets are referred to as DARPA98 and DARPA99, which consist of raw TCP dump data from a simulated medium-sized US Air Force base. The KDD Cup99 dataset was provided for the Knowledge Discovery and Data Mining Tools competition (and associated conference) in 1999. This is a transformed version of the DARPA TCP dump data, consisting of a set of features considered suitable for classification with machine learning algorithms. The data set consists of 41 features, some of which are intrinsic to the network connections, while others are created using domain knowledge.

Classification of Attacks:

The data set in KDD Cup99 have normal and 22 attack type data with 41 features and all generated traffic patterns end with a label either as 'normal' or any type of 'attack' for upcoming analysis. There are varieties of attacks which are entering into the network over a period of time and the attacks are classified into the following four main classes.

- Denial of Service (DoS)
- User to Root (U2R)
- Remote to User (R2L)
- Probing

IV. ALGORITHM

Logistic regression algorithm uses a linear

equation with independent predictor to predict a value. The predicted value can be anywhere between negative infinity to positive infinity. We need the output of the algorithm to be classified variable data. Higher accuracy predicting result is logistic regression model by comparing the best accuracy.

True Positive Rate (TPR) = $TP / (TP + FN)$
False Positive Rate (FPR) = $FP / (FP + TN)$
Accuracy: The Proportion of the total number of predictions that is correct otherwise overall how often the model predicts correctly defaulters and non-defaulters.
Accuracy calculation:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. One may think that, if we have high accuracy then our model is best. Yes, accuracy is a great measure but only when you have symmetric datasets where values of false positive and false negative are almost same.

Precision: The proportion of positive predictions that are actually correct. (When the model predicts default: how often is correct?)
Precision = $TP / (TP + FP)$

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The question that this metric answers is of all passengers that labeled as survived, how many actually survived? High precision relates to the low false positive rate. We have got 0.788 precision which is pretty good.
Recall: The proportion of positive observed values

correctly predicted. (The proportion of actual defaulters that the model will correctly predict)

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

Recall (Sensitivity) - Recall is the ratio of correctly predicted positive observations to the all observations in actual class-yes.

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution.

Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall.

$$\text{General Formula: F-Measure} = 2\text{TP} / (2\text{TP} + \text{FP} + \text{FN})$$

$$\text{F1-Score Formula: F1 Score} = 2 * (\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

V. CONCLUSION

The analytical process started from data cleaning and processing, missing value, exploratory analysis and finally model building and evaluation. The best accuracy on public test set is higher accuracy score will be found out by comparing each algorithm with type of all network attacks for future prediction results by finding best connections. This brings some of the following insights about diagnose the network attack of each new connection. To present a prediction model with the aid of artificial intelligence to improve over human accuracy and provide with the scope of early detection. It can be inferred from this model that, area analysis and use of machine learning technique is useful in developing prediction models that can help to network sectors reduce the long process of diagnosis and eradicate any human error. Our future work can be Network sector want to automate the detecting the attack of packet transfers from eligibility process (realtime) based on the connection detail. Automating this process by show the prediction result in web application or desktop application. Optimizing the work to implement in Artificial Intelligence environment.

Authors' Profile



Mrs. V. Stella Mary pursued Master of Engineering from Anna University, India. Currently she is working as an Assistant Professor in Sri Muthukumaran Institute of Technology. She has worked as an Assistant Professor in reputed engineering colleges under VTU university and Anna University. She has 8 years of teaching experience and 2 years of research experience.



Mrs. M. Vasantha pursued Master of Computer Application from Alagappa University, Master of Engineering from Anna University, India and Doctorate in Computer Science from Mother Teresa University, India in the year 2015. She is currently working as Associate Professor in PG Department of Computer Sciences, Bhaktavatsalam Memorial College For Women, Chennai affiliated with the University of Madras, India since 2016. She has published more than 15 research papers in reputed international journals. Her main research work focuses on Big Data Analytics, Data Mining, and Machine learning. She has 25 years of teaching experience and 10 years of Research Experience.

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