

Network Intrusion Detection System Using various data mining techniques

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Abstract: There are many risk of network attacks in the Internet environment. Nowadays, Security on the internet is a vital issue and therefore, the intrusion detection is one of the major research problem for business and personal networks which resist external attacks. A Network Intrusion Detection System (NIDS) is a software application that monitors the network or system activities for malicious activities and unauthorized access to devices. The goal of designing NIDS is to protect the data's confidentiality and integrity. Our project focuses on these issues with the help of Data Mining. This research paper includes the implementation of different data mining algorithms including Linear regression and K-Means Clustering to automatically generate the rules for classify network activities. A comparative analysis of these techniques to detect intrusions has also been made. To learn the patterns of the attacks, NSL-KDD dataset has been used.

KEYWORDS: Network Intrusion Detection System (IDS), Data Mining Techniques.

I. INTRODUCTION

An Intrusion Detection System (IDS) is a software application that monitor networks or system activities for all the malicious activities and unauthorized access to devices. IDS come in a variety of "flavors" and it aims at detecting suspicious traffic in many ways. There are networks based (NIDS) and host based intrusion detection system (HIDS). There are some IDS devices that detect attacks based on

comparing traffic patterns against a baseline and then looks for anomalies. There are some IDS that simply monitor and alert and there are some IDS which performs an action or actions in response to a detected threat. We will include each of these briefly. Network Intrusion Detection Systems are placed at strategic point or points within the network to monitor traffic to and from all the devices on the network. Ideally you would inspect all the inbound and outbound traffic; however doing so may create bottleneck that would impair the overall speed of the network.

II. DATA SET COLLECTION AND PRE-PROCESSING

A. Data Set Collection

To verify the efficiency and feasibility of the proposed IDS system, we have used NSL-KDD dataset.

It is a brand new version of KDDcup99 dataset. NSL-KDD dataset have some advantages over KDDcup99 dataset. It has solved some of the inherent problems of the KDDcup99, which is considered as the standard benchmark meant for intrusion detection assessment. The training dataset of NSL-KDD is similar to KDDcup99 which consist of approximately 4,900,000 single connection vectors each of which

contain 41 features and are labeled as either normal or attack type, with exactly one specific attack type.

Due to the following reasons, NSL-KDD has turned out to be more popular dataset than KDD cup 99 dataset for intrusion detection purpose[1].

1. Redundant records from the training set are eliminated.
2. Duplicate records from the test sets are removed to enhance the intrusion detection performance.
3. Use of NSL-KDD dataset for classification gives an accurate evaluation of different learning techniques.
4. It is affordable to use NSL-KDD dataset for the experiment purpose and also it consists of reasonable numbers of instances both in the training set as well as in the testing set.

B. Data Set Pre-Processing

Pre-processing is done of original NSL-KDD dataset which is necessary to make it as suitable input for our algorithms. Data set pre-processing is achieved by applying:

- i. Data set transformation
 - ii. Data set normalization
- i) Data set transformation: The training dataset of NSL-KDD which contains approximately 4,900,000 single connection instances. Each of the connection instance contains 42 features including attacks or normal. From these labeled connection instances, we need to convert the nominal features to numeric values so that it is suitable input for classification using data mining techniques[2]. For this transformation, we will be using table 2. Also, we have to assign a numeric value to the last feature within the connection instance which is a target class. For doing this, we have assigned a target class zero for normal

connection and one for any deviation from that (i.e. if that is an attack) as per transformation table 2. In this step, some useless data is filtered and then modified. For example, some text items need to be converted into numeric values. Each and every instance in the dataset has 42 features or attributes including target class shown in Table 1.

**I. TABLE
FEATURES OF NSL-KDD CUP'99 DATASET**

Sr.No	Feature Name
1	Duration
2	Protocol type
3	Service
4	Flag
5	Src bytes
6	Dst bytes
7	Land
8	Wrong fragment
9	Urgent
10	Hot
11	Num failed logins
12	Logged in
13	Num compromised
14	Root shell
15	Su attempted
16	Num root
17	Num file creations
18	Num shells
19	Num access files
20	Num outbound cms
21	Is host login
22	Is guest login
23	Count
24	Srv count
25	Error rate
26	Srv error rate
27	Error rate
28	Srv error rate
29	Same srv rate
30	Diff srv rate
31	Srv iff host rate
32	Dst host count
33	Dst host srv count
34	Dst host same srv rate
35	Dst host diff srv rate
36	Dst host same src port rate
37	Dst host srv diff host rate
38	Dst host error rate
39	Dst host srv error rate
40	Dst host error rate
41	Dst host srv error rate
42	Normal or Attack

An example of original NSL-KDD data set record is shown in figure 1.

[illegible]

Figure 1: The Original NSL KDD cup’99 dataset

II. TABLE TRANSFORMATION TABLE

Type	Feature Name	Numeric Value
Attack or Normal	Normal	0
Attack or Normal	Attack	1
Protocol_type	TCP	2
	UDP	3
	ICMP	4
Flag	OTH	5
	REJ	6
	RSTO	7
	RSTOS0	8
	RSTR	9
	S0	10
	S1	11
	S2	12
	S3	13
	SF	14
	SH	15
Service	All Services	16 to 81

There are numerous nominal values like http, tcp, SF in the dataset. Hence, we have to convert these nominal values to numeric values in advance. For example, service type like "tcp" is mapped to 2, "udp" is mapped to 3, and "icmp" is mapped to 4 and then we will follow Table 2 to transform these nominal values of the dataset features into the numeric values[3]. After transformation, the original NSL-KDD cup'99 dataset will become as shown in Figure 2.

0,2,32,14,491,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,2,0,0,0,0,1,0, 0,150,25,0.17,0.03,0.17,0,0,0,0.05,0,0
0,3,16,14,146,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,13,1,0,0,0,0,0, 08,0.15,0,255,1,0,0.6,0.88,0,0,0,0,0,0

Figure 2: Original NSL- KDD cup'99 dataset after transformation

ii) Data set normalization: Dataset normalization which is considered necessary to enhance the

performance of intrusion detection system when datasets are too large.

Mean normalization is used that makes the values of each feature in the data have zero-mean and unit variance. Normalization refers as the creation of shifted and the scaled versions of statistics, where the intention is that the normalized value allows the comparison of the corresponding normalized values for different datasets in a way that eliminates all the effects of certain gross influence, as in an anomaly time series. Some types of normalization involve only rescaling so that to arrive at the values relative to some size variable. In terms of levels of measurement, such ratios just make sense for *ratio* measurements (where ratios of measurement are meaningful), not *interval* measurements (where only distances are meaningful, but not ratios)[4]. Assume that there are n rows with only seven variables (columns), A, B, C, D, E, F and G, in the data. We use a variable E as an example in the calculations below. The remaining variables in the row are normalized in the same way only.

The normalized value of e_i for variable E in the i^{th} row is calculated as:

$$\text{Normalized}(e_i) = \frac{e_i}{\frac{1}{p} \sum_{j=1}^p e_j}$$

Where,

p = it is the number of records that is used to calculate the mean.

III. Application of Algorithms

- i. **Linear Regression:**
 - Σ Study of linear relationship between an output variable and one or more input features.
 - Σ For a linear model, our hypothesis is of the form,
$$h_{\theta}(x) = \theta_0 + \theta_1 x \text{ or } h_{\theta}(x) = \theta^T x.$$

Σ We have to adjust θ_0 and θ_1 so that $h_{\theta}(x)$ is close to y .

For that we define an error function,

$$J(\theta_0, \theta_1) = (1 / 2m) * \sum_{i=1}^m (h_{\theta}(x^i) - y^i)^2.$$

Σ To minimize the error, we use Gradient Descent Algorithm,

Repeat until convergence $\{\theta_j = \theta_j -$

$$\alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1) \text{ for } j=0 \text{ and } j=1\}$$

(ii) K-Means Clustering

- It is an algorithm to categorize or to group all the objects based on the attributes/features into K number of groups.
- The grouping which is done by minimizing the sum of the square of distances between data and the corresponding cluster centroid.[5]
- Algorithm
Randomly initialize the K cluster centroids
Repeat {
 for $i=1$ to m
 $c(i) := j$ that minimizes $\|x(i) - \mu_j\|^2$,
 for $k=1$ to K
 μ_k = average mean of the points assigned to cluster k . [6]

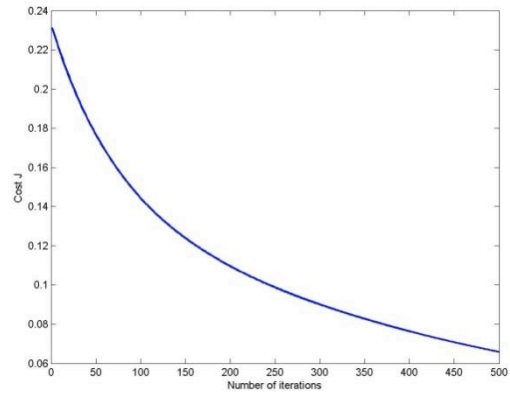
IV. Results

1. Linear Regression Results:

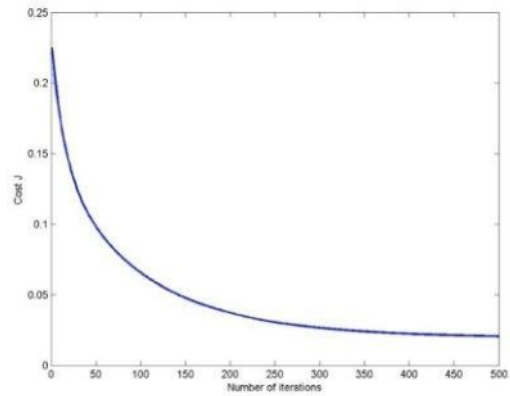
For different values of alpha, linear regression algorithm was trained to find the best result.

Alpha(α)	0.00	0.00	0.01	0.03	0.1	1
	1	5				
Accuracy (%)	79.20	80.14	71.47	70.98	69.65	65.5

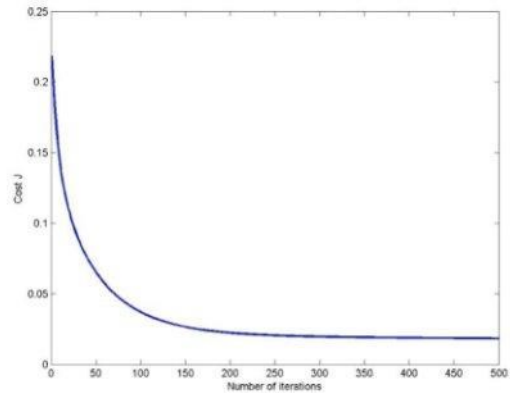
Σ Cost Variations (alpha = 0.001)



Σ Cost Variation (alpha = 0.005)



Σ Cost Variation (alpha = 0.01)

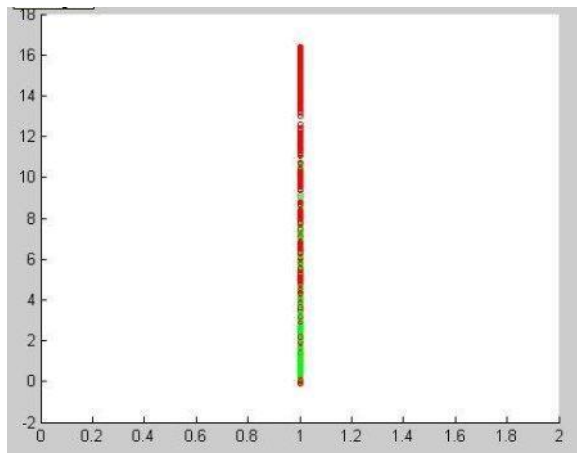


2. K-means Clustering Results:

Σ We used two clusters, one to classify attacks and other for normal patterns.

- Σ Random centroids were selected and there results were compared.
- Σ Best centroid value was found to be $X(i) = 84252, :)$ and $X(j) = 17428, :)$
- Σ Accuracy was found 67.53%.

Cluster Plot



V. Conclusions

Algorithms based on Data Mining were implemented successfully showing different accuracies..NSL-KDD dataset was preprocessed using mean normalization method.Linear regression, surprisingly, proved to be very effective in detecting network attacks with a 80% accuracy. K-Means Clustering being a semi-supervised approach showed decent results with a 67.5 % accuracy.

VI. FUTURE WORKS

- Σ Network Intrusion Detection can be improved using latest data mining techniques like deep neural network, dbscan etc.
- Σ Here we have not used feature selection to select only relevant features. Using feature selection time performance can be improved as well as accuracy.
- Σ Dimensionality Reduction using principal component analysis can be used to improve the time and visualization.
- Σ The NSL-KDD dataset is very old and there are some bugs which can be tackled using a well derived dataset.

VII. References

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