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MODIFYING MLP TECHNIQUE TO IMPROVE EFFICIENCY OF ANOMALY BASED INTRUSION DETECTION SYSTEM

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Abstract

To monitor computer system for indication of security violations over any network and cloud environment IDS are used. Resting on detection of such indication triggers of IDSs is to details to get the alerts. These alerts are straightforward to urge to an individual's analyst who assess them and starts an enough response. situate into be relevant, IDSs are ascertained to trigger thousands of alerts for every day, basically of that are incorrectly triggered by begin events equivalent to false positive. This build it really not easy for the analyst to properly recognize alerts related to attack such as a true positive. We present Neural Network primarily based supervised Conjugate Gradient Methodology based MLP Technique and compare with Back propagation algorithmic rule for intrusion detection. Modified MLP Technique removes the deficiency of BP Algorithm. The advantage of Neural Network based unsupervised to in identifying new or unseen attack.

***Key words: Support vector Machine, attack*, intrusion detection system, MLP Technique.**

INTRODUCTION

There are regularly two class of approach taken to intrusion detection, first Misuse Detection depends on the pre-recording depiction of precise permitting any matches to them in existing activity to then be patterns for intrusions reported. Patterns equivalent to illustrious attacks are called signatures. A classifier is then trained to categorize one category from the other, supported on network traffic attributes. [3] Planned a data-mining framework for such a system. They used a series of information mining techniques, comparable to frequent episodes and association rules, to help extract discriminative options that embody several network traffic statistics. Get properly- labeled knowledge instances, while, is difficult and time intensive, considerably for whole bright new attack varieties and patterns [13] On the alternatively Anomaly Detection amount to work models for usual traffic activities therefore categorized as intrusions any network behavior that widely diverge from the known traditional patterns.

Traditional techniques of network intrusion detection square measure base on the saved patterns of known attacks. They observe intrusion by match up to the network association options to the attack pattern that square measure provided by human experts [4].

The major drawback of ancient strategies is that they can't establish unknown intrusion. albeit a replacement pattern of the attacks were discovered, this new pattern would need to be manually updated into system. It's still in a position of recognizing new attacks to a point of similitude to the learned ones, the neural networks area unit wide thought-about as associate degree economical approach to adaptively classify patterns, however their high computation intensity and also the long coaching cycles greatly hinder their applications, particularly for the intrusion detection downside, wherever the number of connected knowledge is extremely necessary. During this paper our object to suggested a Neural Network primarily based formula that is accomplished finding unseen attack and establish new attack.

LITERATURE SURVEY

A lot of research works have been carried out in the literature for intrusion detection and some of them have motivated us to take up this research. Brief reviews of some of those recent significant researches are presented below:

Manoranjan Pradhan[1] Here we tend to required to distinguish if a neural network is capable to recognize regular traffic properly, and detect acknowledged and unknown attacks without using a massive amount of training data. For the training and testing of the neural network, we tend to use the DARPA intrusion detection analysis knowledge Data set.

Jianliang Meng[2] With the help of improve bp algorithm which is based on Cauchy error Estimator detecting low detection efficiency and high error rate and undetected rate and so on.

Byoung-Doo[3] Built IDS deals well numerous mutated attacks, similarly as well-known attacks by victimization. Time Delay Neural Network classifier that discriminates between traditional and abnormal packet flows.

Tsong and et al.[4] initiate a three-tier design of intrusion detection system that consists of a blacklist, a white list and a multiclass support vector machine classifier. They meant a three-tier IDS supported the KDD'99 benchmark dataset.

Weiming and et al[5] Proposed an intrusion detection algo supported on that the AdaBoost Method, The Discrete AdaBoost method was selected to learn The Object.

Hu Zhengbing1 and et al [6] planned an algorithmic programmed to use the better known signature to search out

the signature of the connected attack rapidly. They used 9 different-sized databases,

Tich Phu oc Tran et al [7] have applied Machine Learning techniques to resolve Intrusion Detection problems inside computer networks. Due to complex and dynamic nature of computer networks and hacking techniques, identifying malicious behavior remains a challenging task for security experts, that is, defense systems that were presently obtainable undergo from low detection ability and high number of false alarms.

Ye Yuan et al. [8] proposed a method of evidence assignment in combination with Dempster-Shafer theory to identify network attack data. In this method, extracted features were identified by a multigeneralized regression neural network classifier, which determined the basic probability assignment.

Snehal A et al. [9] presenting decision tree based algorithm to make a multiclass intrusion detection system. Support Vector Machines was the classifiers which were initially designed for binary classification. The classification applications could solve multi-class problems. This method could reduce the training and testing time, increasing the efficiency of the system.

Shun J and Malki H. A. [10] represented a neural network-based intrusion detection method for the internet-based attacks on a electronic network. Intrusion detection systems (IDS) had been produced to expect and prevent current and future attacks.

Muna Mhammad T. and Monica [11] presented an intrusion detection model truly supported on hybrid fuzzy logic and neural network. The model had capability to identify an attack, to discriminate one attack as of any more i.e. ordering attack, and the most part dynamic, to perceive new attacks with high detection rate and little false negative.

Aida O. Ali et al. [12] did a relative study between the performances of recent nine artificial neural networks (ANNs) based classifiers was assessed, centered on a particular set of features.

LEE, et.al. [13] Proposed a data-mining framework for such a system. They used a series of knowledge mining techniques, corresponding to frequent episodes and association rules, to assist extract discriminative options that embody numerous network traffic statistics.

Jamal Esmaily[14] With the help of Machine Learning and Data Mining Techniques, Intrusion Detection Systems(IDS) are able to diagnose attacks and system anomalies more effectively.

IDS BACKGROUND

Intrusion Detection System (IDS) perpetually monitors actions in a very sure surroundings and decides whether or not they area unit a part of a potential hostile attack or a legitimate use of the surroundings. The surroundings is also a laptop, many computers connected in a network or the network itself.

3.1 Intrusion Detection System

The IDS analyzes numerous styles of info regarding actions emanating from the surroundings and evaluates the likelihood that they're symptoms of intrusions. Such info includes, parenthetically, configuration info regarding this state of the system, audit info describing the events that occur within the system. These measures embrace accuracy, completeness, performance, efficiency, fault tolerance, timeliness, and adaptively. The additional wide used measures area unit-

The True Positive (TP) rate, that is, the share of intrusive actions (e.g., error connected pages) detected by the system, False Positive (FP) rate that is that the share of traditional actions (e.g., pages viewed by traditional users) the system incorrectly identifies as intrusive, and Accuracy that is that the share of alarms found to represent abnormal behavior out of the whole variety of alarms. Within the current analysis TP, FP and Accuracy measures were adopted to judge the performance of the new methodology. There area unit IDS that merely monitor associated alert and there area unit IDS that perform an action or actions in response to a detected threat. We'll cowl every of those in brief.

3.2 Require for Intrusion Detection System

An automatic data processing system ought to offer confidentiality, integrity and assurance against denial of service. However, because of hyperbolic property (especially on the Internet), and also the hug spectrum of monetary potentialities that area unit gap up, additional and additional systems area unit subject to attack by intruders. This subversion tries attempting to exploit flaws within the OS likewise as in application programs and have resulted in spectacular incidents just like the net Worm incident of 1988.

That's the 2 ways that to handle subversion tries in WSN. A way is to forestall subversion itself by building a very secure system. We could, parenthetically, need all users to spot and certify themselves; we tend to might shield information by numerous cryptological ways and extremely tight access management mechanisms. but this is often not extremely possible because:

In apply; it's unacceptable to make a very secure system. Miller provides a compelling report on bugs in widespread programs and operational systems that appears to point that (a) bug free code continues to be a dream and (b) no-one appears to require to create the hassle to do to develop such code. excluding the very fact that we tend to don't appear to be obtaining our money's value after we purchase code, there also are security implications once our E-mail code, parenthetically, are often attacked. coming up with and implementing a very secure system is therefore a very troublesome task.

The enormous put in base of systems worldwide guarantees that any transition to a secure system, (if it's ever developed) is going to be long in returning. Cryptological ways have their own issues. Passwords are often cracked, users will lose their passwords, and full crypto-systems are often broken. Even a really secure system is prone to abuse by insiders UN agency abuse their privileges. It's been seen that that the connection between the amounts of access management associated user potency is an inverse one, which suggests that the stricter the mechanisms, the lower the potency becomes.

The history of security analysis has educated North American country a valuable lesson – irrespective of what number intrusion interference measures area unit inserted in a very network, there are perpetually some weak links that one might exploit to interrupt in.

We therefore see that we tend to area unit cursed systems that have vulnerabilities for a short while to return. If there attacks on a system, we might prefer to discover them as presently as potential (preferably in real-time) and take acceptable action. This is often primarily what associate Intrusion Detection System (IDS) will in WSN. Associate IDS doesn't typically take preventive measures once associate attack is detected; it's a reactive instead of pro-active agent. It plays the role of associate informant instead of a policeman.

PROBLEM IDENTIFICATION IN INSTRUCTION DETECTION SYSTEM

Traditional methods of network intrusion detection are based on the kept patterns of recognized attacks. They perceive intrusion by linking the network connection structures to the attack pattern that are providing by humanoid experts. The main disadvantage of traditional methods is that they cannot detect unidentified intrusion. Even if a new pattern of the attacks were exposed, this new pattern would have to be physically efficient into system. It is also accomplished of identifying new attacks to some degree of similarity to the learned ones, the neural networks are extensively measured as an effectual method to adaptively categorize patterns, but their high computation strength and the long training cycles greatly delay their applications, particularly for the intrusion detection problem, where the amount of related data is very important. There are some recorded frequent major deficits with traditional intrusion detection systems. With the help of data mining methods, these problems can be easily overwhelmed. Briefly, the Neural Network methods have providing the following benefits:

• **Enhanced variations detection**:- This is particularly true for anomaly detection. Not defective to pre-defined signatures, the anxiety with variations is not as much as earlier, since any unconventionality from a unique (normal) signature will be preserved as intrusion, counting those before unknown variations of intrusions.

• **Measured false alarms:-** yet though these are false positives, thru a learning process to recognize recurrent orders of false alarms, it is probable for us to mesh those usual system activities and maintain the rate of false alarms at an suitable level.

• **Condensed false notices**.- With data mining methods, patterns (or signatures) of normal activities and irregular events (intrusions) can be created automatically. It is also conceivable to present new types of attacks through an incremental learning procedure. As a effect, more and more attacks can be perceived correctly. This leads to a compacted number of false notices.

• **Enhanced efficiency**:- One extremely attractive characteristic of data mining techniques is that the ability to extract most important information out of enormous amounts of data. when a step of feature removal and/or feature choice, the knowledge method may be done way more competently.

CONVENTIONAL TECHNIQUE FOR IDS

The back propagation algorithm programs inculcate a particular feed-forward multilayer neural network intended for a specified set of input patterns within recognizable classifications.

5.1 Standard Back Propagation Algorithm:

BP is one of the humblest and most general methods. The elementary BP algorithm works as follows:

1. Major all the assembly weights W with small random values from a pseudorandom order producer.

2. Recurrence until meeting (also when the error E is below a predetermined value or until the gradient VE(t)/VW is smaller than a preset value).

2.1 Calculate the update using

$$\Delta W(t) = -\eta \frac{\partial E(t)}{\partial W}$$

2.2 Update the weights with

$$\mathbf{W(t+1) = W(t)+\Delta W(t)}$$

2.3 Compute the error E(t+1).

Wherever t is the iteration number, W is the connection weight, and h is the learning rate. The error E can be selected as the mean square error (MSE) function among the actual output yj and the desired output dj:

$$E = \frac{1}{2}\sum_{j=1}^{n}(d_j - y_j)^2$$

An incremental approach is more effectual than batch training approach and also faster for systems with large training samples, as random conflicts can be encouraged to help the system to escape from a local minimum point.

Problem of Back propagation algorithm

The BP algorithm defined above has some faults. If the learning rate is set small adequate to minimize the total error, the learning procedure will be slowed down. On the other hand, a larger learning rate may speed up learning procedure at the risk of latent alternation. Another problem is that, fractional negligible points or even stages on error external are often encountered throughout the learning. We recommend

Neural Network based algorithms for network intrusion detection to detect unseen attack.

PROPOSED APPROCH

In This segment we have to present feed word neural network architecture that is used to compress image in the research works.

6.1 Multilayer perceptron algorithm

MLP algorithm [14] is a widely used learning algorithm in ANN. The Feed-Forward Neural space is capable of approximating most issues with high accuracy and generalization ability. MLP is the classifier algorithm. It works on basic principle of joining an every previous layer of neuron's output of the to the input of every neuron's to the next layer. Feed-Forward Neural Network is the based on the error-correction learning rule. Error propagation mainly consists of two passes, a forward pass, and a backward pass through the different layers of the network. In Forward pass computes 'functional signal', feed forward propogation of input pattern signals through network. And the Backward pass is the weights are adjusted with respect the error correction rule. The error signal generated as a difference through the network.

ALGORITHM:

The rule for Perceptron Learning is predicated on the back-propagation rule mentioned antecedently. This rule will be coded in any programming language, and within the case of this tutorial, Java for the applets. During this case we tend to are assumptive the utilization of the sigmoid perform f(net) represented within the tutorial. This can be as a result of it's an easy spinoff.

Algorithm:

1. Initialize weights and threshold.

Set all weights and thresholds to small random values.

2. Present input and preferred output

Here input $X_p = x_0, x_1, x_2, \ldots, x_{n-1}$ and target output $T_p = t_0, t_1, \ldots, t_{m-1}$ where n is that the series of input nodes and m is that the series of output nodes. Set w_0 to be **-ø**, the bias, and x_0 to be continually one. For pattern association, Xp and Tp correspond to the patterns to be related. For categorization, Tp is place to zero aside from one part set to one that corresponds to the category that Xp is in.

Compute the actual output

Every layer calculates the following:

$$y_{pj} = f\,[w_0x_0 + w_1x_1 + \ldots + w_nx_n]$$

This is then passes to the next layer as an input. The final layer outputs values o_{pj}.

3. Adapt weights

Beginning from the output we have a tendency to presently work backwards.

$$w_{ij}(t+1) = w_{ij}(t) + \tilde{n}\eth_{pj}o_{pj},$$

where ñ could be a gain term and $\eth_{pj}$ is a error term for pattern **p** on node **j**

4. For output units

$$\eth_{pj} = ko_{pj}(1 - o_{pj})(t - o_{pj})$$

For hidden units

$$\eth_{pj} = ko_{pj}(1 - o_{pj})[(\eth_{p0}w_{j0} + \eth_{p1}w_{j1} + \ldots + \eth_{pk}w_{jk})]$$

where the sum (in the [brackets]) is in excess of the **k** nodes in the layer over node **j**.

5. Produce an easy dominance of the class of Near to neighbors as the forecast value estimation of the new model.

6.2 Conjugate Gradient Multi-Layer Perceptrons(CMLP)

Given a vector Δw_0 in the weight space, a second-order Taylor series approximation of the error function around this vector is expressed as

$$E(w)=E(w_0)+d^T\Delta+1/2(\Delta w)^T H\Delta w$$

Where, d & H, are the gradient vector and the Hessian matrix, respectively. The minima of the function E are located where the gradient of E was equal to zero, therefore, the optimal value of w is given by

$$w = w_0\text{-}H^{-1}d$$

The form of the basic updating equation of the CG algorithm is the same as the general gradient algorithm, and is given by

$$w(k+1)=w(k)+\eta(k)\Delta w(k)$$

Where h (*k*) is a time-varying learning parameter that may be updated using the following line search method:

$$\eta(k) = \min\nolimits_{\eta}\{E(w(k)+\eta(k)\Delta w(k)\}$$

The conjugate condition for the incremental weight vector D*w* is designed

$$(\Delta w(k))^T H(k)\Delta w(k+1) = 0$$

where the Hessian matrix *H*(*k*) is calculated at the point *w*(*k*) . The updating for *w*(*k*) , in this case, is chosen as:

$$\Delta w(k) = -d(k)+\alpha(k-1)\Delta w(k-1)$$

In order to satisfy the conjugate condition between the vectors D*w*(*k*) and D*w*(*k* +1) , the update procedure fora (*k*) is expressed using the Fletcher-Reeves formulation, the Hestenes-Stiefel formulation and the Hestenes-Stiefel formulation given by equation respectively:

$$\alpha(k) = \frac{(d(k+1))^T d(k+1)}{(d(k))^T d(k)}$$

$$\alpha(k) = \frac{(d(k+1))^T (d(k+1) - d(k))}{(d(k))^T d(k)}$$

$$\alpha(k) = \frac{[d(k) - d(k-1)]^T d(k))}{(\Delta w(k-1))^T [d(k) - d(k-1)]}$$

In fact, this algorithm exploits information about the direction of search for D_w from the previous iteration in order to accelerate the convergence

6.3 Assessment Measures

To Assess the system performance the following measures were used.

True Positive Rate (TP) (also known as Detection Rate or Completeness):The number of Attack records which were correctly classified as Attack.

False Positive Rate (FP): the number of Normal records which incorrectly were classified Attack.

6.4 Data Set Description

Because the goal of this work is to study and enhance the learning capabilities of the Artificial Immune System techniques for intrusions detection, the Negative Selection Algorithm is compared to a neural network based algorithm that use the full set of samples from the KDD Cup99 dataset and witch contain 5000 sample. The original data set contain 5 million records which specify various attacks in which 1% sample consisting of about 5000 records was used in our experiment.

6.5 Data Preprocessing

In K-DD-99 data set, each records representing a connection between two networks host according to some well defined network protocol. Each connection is represented by 41 features, which include the basic features of individual of TCP Connections, the content features, No. of byte, Transferred byte etc. the features in column 2 in KDD-99 Data set are transmitted byte, flag. We are interested in anomaly detection via unsupervised Learning algorithm. Hence all the records labeled as attack were considered as intrusion, while remaining was considered as normal. The labels used for evaluating the detection performance of the algorithm.

6.6 Empirical Setting

The BackPropagation Algorithm are written in visual basic.Net 2008 as front-end and MS-Access used as Backend and compiled into mix files. Modified MLP Algorithm algorithms are relatively efficient due to vectored programming and active optimization. All experiments are run on a PC with a 3.06GHz Pentium-4 CPU with 1GB DRAM and running Windows XP. For the Negative Selection Algorithm, the learning rate follows m = 0.5.

In order to study the effect of the total number of data base on the intrusion detection results, we performed empirical studies with 5000 data set.. The Error Value of each algorithm is also recorded and compared. Each experiment is run five times for evaluating intrusion detection results, we report the detection rate .The false positive rate is the percentage of normal instances that are labeled as attacks. The attack detection rate represents the percentage of all attack instances that are detected, i.e., labeled as attacks. We also report in Graph, by varying the parameter used in the detection method, to show the tradeoff between the false positive rate and the detection rate.

6.7 Experiment Results and Analysis

Now, we compare the aforementioned clustering algorithms on the whole data set with 5000 data set The Error Value for the these algorithms are shown in Table 6.1 respectively.

Experiment 1:

In this experiment 1, we investigate Error value parameter of Modified MLP Algorithm and Back propagation algorithm. In the training phase, Modified MLP Algorithm was used to train the data. After training, each data was labeled according to the majority type of data. For instance, if more than 50% of the connections in database were intrusions, and its centroid weight vector would be labeled as intrusion. Modified MLP Algorithm perform significantly better (p < 5%) than the others in terms of Error Value with much less run time. This experiment is run on individual Sigmoid Value for each KDD99 Data set. This data set contain only numeric value not categorical valued. Modified MLP Algorithm fast than Back propagation algorithm.

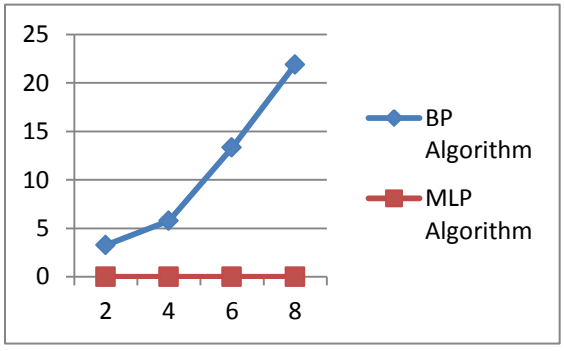

Fig (6.1) **results with 100 Iterations Value with Error parameter efficiency**

The experiments were conducted in 3 components. The preliminary experiment was conducted to visualize several (what percentage| what number) iterations and the way many hidden units that was required before the neural network was

properly trained. The second and therefore the final experiments were conducted to visualize (what percentage what number) percent of the traditional traffic and therefore the attacks that were classified correctly.

Table (6.1): Summary Detection results

Sigmoid Alpha Value	Algorithm	
	BP Algorithm Detection Rate	Modified MLP Algorithm Detection Rate
2	55	78
4	57	80
6	43	93
8	59	91

Experiment 2:

Now we discover the detection rate of BP algo and Modified MLP algo. To assess the accuracy of a system, we tend to use 2 indicators that were used in: Detection Rate (DR) and False Alarm Rate (FAR).

DR equals the amount of intrusions divided by the entire number of intrusions within the data set.

FAR equals the amount of traditional instances divided by the amount of traditional instances within the information set.

(6.2): Summary Detection results

Sigmoid alpha Value	Algorithm	
	BP Algorithm	Modified MLP Algorithm
	Error Value	Error Value
2	3.271	0.006409
4	5.782	0.001706
6	13.310	0.000840
8	21.870	0.000441

The table (6.2) shows that BP Algorithm has low detection rate than Modified MLP Algorithm. Modified MLP algorithm is used in intrusion detection system is so good when it has low false positive rate and high Detection rate. Negative Selection Algorithm map reduce the false positive and it has high detection rate for detect the unseen or new attack. The graph for the BP Algorithm and Modified MLP Algorithm are omitted for comprehensibility and better visualization, particularly because they are visibly.

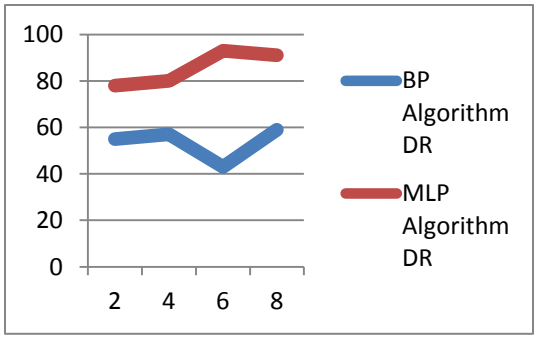

Fig. (6.2): **Graph for Detection Rate on 100 clusters**

Fig. (6.2) Show the Graph for detection rate of the BP algorithms and Modified MLP Algorithm 8 Sigmoid Alpha Value respectively. It can be seen that for 8 Sigmoid Alpha Value, Modified MLP Algorithm has high detection rate than BP Algorithm. Modified MLP Algorithm clusters performs extremely well at very low false positive rates, it can detect more than 92% attacks with a false positive rate of almost 0.2%. Overall, the Modified MLP Algorithm better ones and stable across different Number of Sigmoid Alpha Value.

CONCLUSION

In this researched paper we discussed a neural network based intrusion detection system, here we presented and classify in normal attack and pattern based. Thus we applied CMLP method that has increased the generalization capability of the neural network and at the same time decreased the training time. We have to justify that the long training time of the neural network was mostly due to the huge number of training vectors of computation facilities. After all *online* classifier for the attack types that it has been trained for as on the neural network based IDS can operate. The only issue that creates the neural network off-line is that the time used for gathering info necessary to compute the features.

In this paper we introduce MLP in a IDS to protect user. This algorithm is intended to be scalable by allowing different format of data to apply into MLP for more reliable IDS solution. The implemented MLP is just a first step in the direction of a complex CIDS. An interesting future topic is the implementation of the fully functional CMLP on the real internet testbed and cloud infrastructure. To essentially apply the preparation, performance and quantifiability problems have to be compelled to be thought of because the next step.

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