

BBB

koeradoera CCC

BBB

*Thesis submitted to the
Indian Institute of Information Technology Guwahati
for award of the degree*

of

Master of Technology

by

koeradoera CCC

under the supervision of

Dr. AAAAA BBB



**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
INDIAN INSTITUTE OF INFORMATION TECHNOLOGY GUWAHATI**

May 2020

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Dr. AAAAA BBB,
Assistant Professor,
Department of Computer Science and Engineering
somewhere

Date:

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ABSTRACT

[illegible]

List of Abbreviations

SaaS	Software as a Service
S3	Amazon Storage Service
SOA	Service Oriented Architecture.
SWS	Simple Workflow Service
SLA	Service Level Agreement
VM	Virtual Machine
VPC	Virtual Private Cloud

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Chapter 1

Introduction

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random thing . Finally, we conclude in **Chapter 5** Some random thing Some random thing
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Literature Review

2.1 Deployment Models of Clouds

5

2.1.1.1 IaaS

[illegible]

2.1.1.2 PaaS

[illegible]

2.1.1.3 SaaS

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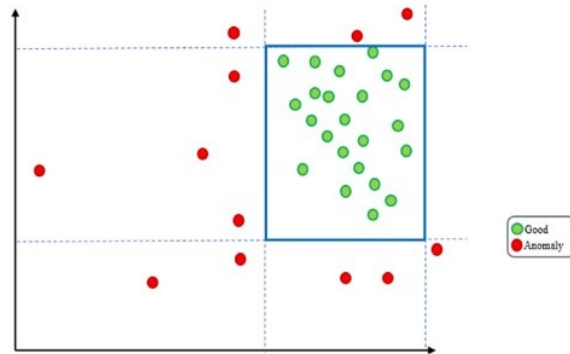


Figure 2.2: Simple Anomaly [?]

Some random thing Some random thing Some random thing Some random thing Some ran-
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2.3.1 Global anomaly

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2.3.2 Contextual Anomaly

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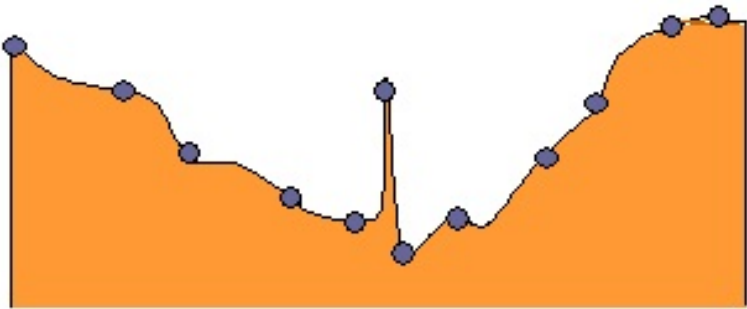


Figure 2.3: Global Anomaly [?]

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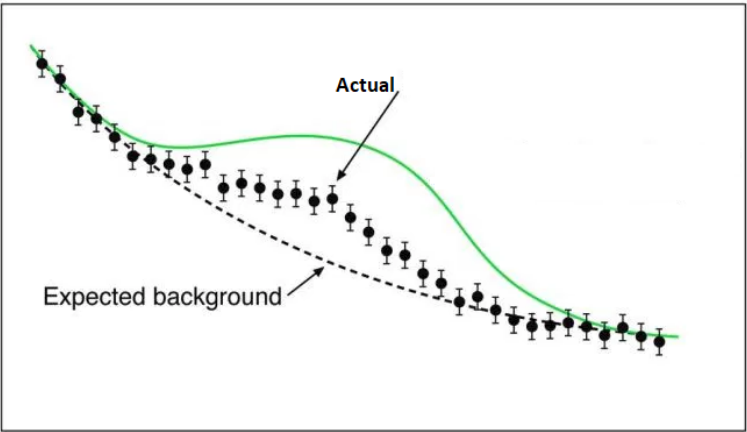


Figure 2.4: Contextual Anomaly Example [?]

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2.3.3 Collective Anomaly

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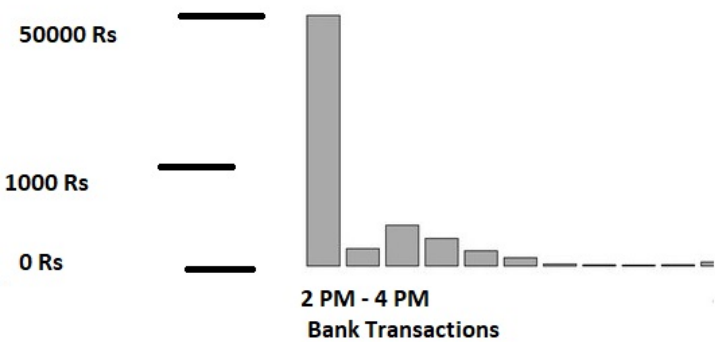


Figure 2.5: Collective Anomaly [?]

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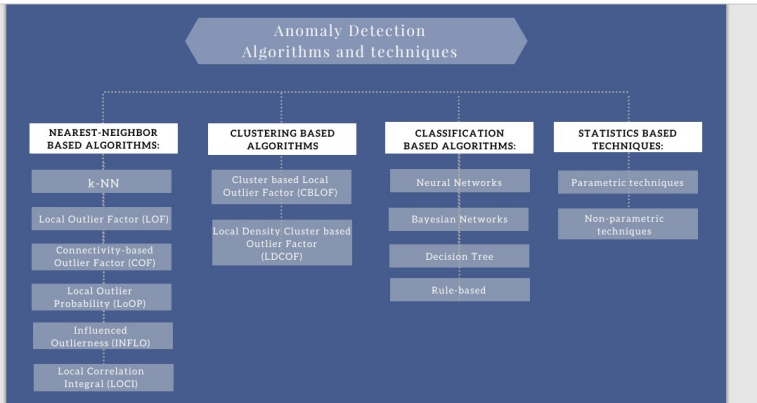


Figure 2.6: Anomaly Detection Algorithms [?]

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2.3.7 Anomaly detection algorithms categories

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2.3.7.1 K-nearest neighbor: k-NN

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2.3.7.2 Local Outlier Factor (LOF)

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2.3.7.3 K-means

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The user has to define the number of clusters in the early beginning. Some random thing Some
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2.3.7.4 Support Vector Machine (SVM)

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2.3.7.5 Neural Networks Based Anomaly Detection

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Table 2.1: Anomaly Detection Algorithms comparison [?]

Algorithm	Pros	Cons
<ul style="list-style-type: none"> • K Nearest Neighbour • K-NN 	<ol style="list-style-type: none"> 1. Very easy to understand 2. Good for creating models that include non standard data types such as text 	<p>Large Storage requirements</p> <p>Computationally Expensive</p> <p>Sensitive to the choice of the similarity function for comparing instances</p>
Local Outlier Factor(LOF)	Well-known and good algorithm for local anomaly detection	<p>Only relies on its direct neighborhood .</p> <p>Perform poorly on data sets with global anomalies.</p>
K Means	<p>Low Complexity</p> <p>Very easy to implement</p>	<p>Each cluster has pretty equal number of observations</p> <p>Necessity of specifying K</p> <p>Only work with numerical data</p>
Support Vector Machine (SVM)	<p>Find the best separation hyper-plane.Deal with very high dimensional data.</p> <p>Can learn very elaborate concepts. Work very well</p>	<p>Require both positive and negative examples. Require lots of memory.</p> <p>Some numerical stability problems.Need to select a good kernel function</p>
Neural networks based anomaly detection	<p>Learns and does not need to be reprogrammed.</p> <p>Can be implemented in any application</p>	<p>Needs training to operate</p> <p>Requires high processing time for large neural networks</p> <p>The architecture needs to be emulated</p>

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Chapter 3

First Contribution

Movement of services is essential for IT employees and other employees it increases the flexibility. Ever increasing modernization increases challenges for IT professionals in terms of new demands and complexities for keeping the organization secure. It is difficult to get the full benefit of cloud apps and services, an IT team must find the right combination of supporting technologies while maintaining control to protect critical data. Day by day with increasing challenges keeping the systems secure and maintaining their integrity has been a challenging task. This paper studies various anomaly detection techniques used by cloud service providers and various approaches which exist in literature and discusses the anomaly detection techniques using KDD data set.

Keywords: Cloud, Virtualization, Time Series Analysis, Anomaly Detection, Distance Based Clustering

3.1 Outlier Detection

Any deviation from normal is considered an anomaly. Outlier detection (also known as anomaly detection) is the process of finding data objects with behaviors that are very different from expectation. Such objects are called outliers or anomalies. The most interesting objects are those, that deviates significantly from the normal object. Outliers are not being generated by the same mechanism as rest of the data. [?]

3.2 Security Framework

In Cloud Computing services security is a series of documented processes and frameworks. Which revolves around defining policies and procedures around the implementation. For any successful

security implementation of security frame work we need to define policies and procedures with respect to cloud. The main point of having a frame work is to reduce the risk levels and organizations exposure to vulnerabilities.

Control the use of apps: First we identify the cloud apps, various cloud apps can be using infrastructure as a service, or platform as a service services used by your organization. One needs to study usage patterns, identify the risk levels and business readiness of apps against risks. Start managing them to ensure security and compliance. [?] To protect your sensitive information anywhere in the cloud: understand, classify, and protect the exposure of sensitive information at rest. Apply out-of-the box policies and automated processes to apply controls in real-time across all your cloud apps. Then protect against cyber threats and anomalies: Detect unusual usage patterns analyzed by behavior of app usage across cloud to identify ransomware, currency mining, compromised users or fake applications, analyze high-risk usage and remediate automatically to limit the risk to your organization. In this process you need to assess the compliance of your cloud apps: Assess if your cloud apps meet relevant compliance requirements including regulatory bodies and industry standards. Prevent data leaks to non-compliant apps, and limit access to regulated data. When an organization elects to store data or host applications on the public cloud, it loses its ability to have physical access to the servers hosting its information. As a result, potentially sensitive data is at risk from insider attacks. The extensive use of virtualization in implementing cloud infrastructure brings unique security concerns for customers or tenants of a public cloud service. Virtualization affects the relationship between the operating system and underlying hardware – be it networking, storage or even computing. This introduces an additional layer – virtualization – that itself must be properly configured, managed and secured. Security in Microsoft Systems is done based via policies in accounts. To create policies go to control inside it go to templates. Select a policy template from the list, and then choose (+) Create policy. Customize the policy (select filters, actions, and other settings), and then choose Create. On the Policies tab, choose the policy to see the relevant matches (activities, files, alerts). Tip: To cover all your cloud environment security scenarios, create a policy for each risk category. How can policies help your organization? You can use policies to help you monitor trends, see security threats, and generate customized reports and alerts. With policies, you can create governance actions, and set data loss prevention and file-sharing controls.

3.3 How Microsoft Detects Anomaly in Azure

Microsoft uses a technology called security center [?] in its cloud environments. To detect threats and reduce false positives Security Center collects data from Azure resources and network and

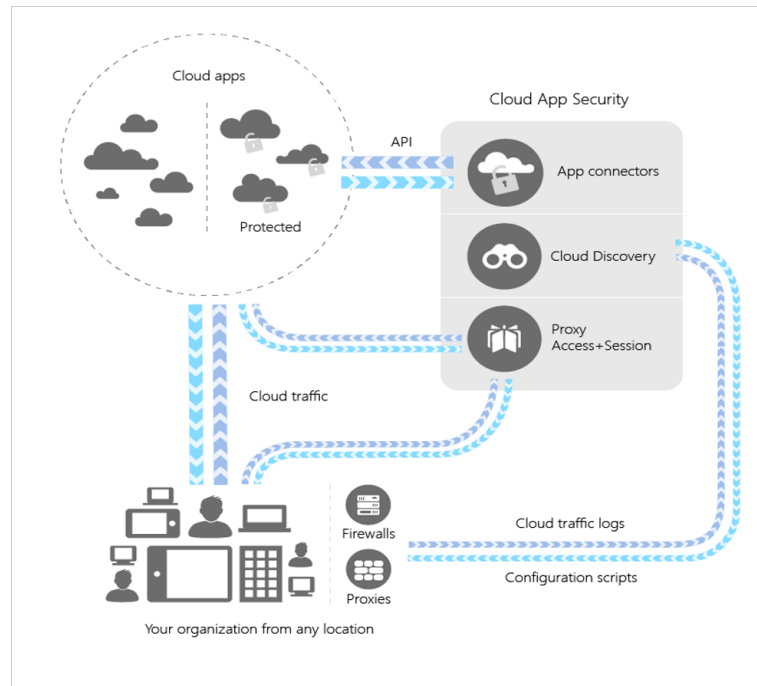


Figure 3.1: Security architecture [?]

then applies a lot of machine learning and big data algorithms to detect threat. These techniques are more advanced than normal signature-based anomaly detection techniques. It is impossible to manually identify the attack and predict the attack when it might happen. So the Microsoft Security Center uses the following technologies:

1. Intelligent Threat Intelligence
2. Behavioral Analytics
3. Fusion Analytics

3.3.1 Intelligent Threat Intelligence

It looks for bad actors by using the information obtained via Microsoft Products and services, Microsoft Digital Crimes Unit and Microsoft Security Response Centre along with external feeds. Microsoft has an immense amount of global threat intelligence. Telemetry flows in from multiple sources, such as Azure, Office 365, Microsoft CRM online, Microsoft Dynamics AX, outlook.com, MSN.com, the Microsoft Digital Crimes Unit (DCU), and Microsoft Security Response Center (MSRC). Researchers also receive threat intelligence information that is shared among major

cloud service providers and feeds from other third parties. Azure Security Center can use this information to alert you to threats from known bad actors.

3.3.2 Behavioral Analytics

Behavioral analytics is a technique that analyses and compares data to a collection of known patterns. However, these patterns are not simple signatures. They are determined through complex machine learning algorithms that are applied to massive datasets. They are also determined through careful analysis of malicious behaviors by expert analysts. Azure Security Center can use behavioral analytics to identify compromised resources based on analysis of virtual machine logs, virtual network device logs, fabric logs, crash dumps, and other sources. In addition, there's correlation with other signals to check for supporting evidence of a widespread campaign. This correlation helps to identify events that are consistent with established indicators of compromise.

3.3.3 Fusion Analytics

It uses statistical techniques to build a historical data which is based on usage patterns and any deviation from normal alerts those deviations [?] and it creates a baseline which if confirms to a potential attack vector then the particular usage is detected as an anomaly and in turn thus could be a security event.

Security Centre in Azure also works with connected partner solutions, like firewall and endpoint protection solutions. Microsoft uses **Fusion Analytics** [?] as the backbone of Security Centre's anomaly detection system. Fusion works by looking at various kind of alerts generated in Microsoft Azure ecosystem and then it tries to find pattern which could reveal attack progression indicating what should be next course of action.

3.4 How Amazon Finds Anomalies in AWS

Amazon uses a technology called guard duty [?]. This service continuously monitors for threat detection service and continuously monitors bad behavior and protects aws accounts and workloads. In the cloud related services collection and aggregation of network related information and activities is simplified, but it is time consuming for security teams to continuously analyses event log data for potential threats. With the help of Guard Duty now you have an cost effective and intelligent solution which is used for threat detection in AWS cloud. Guard Duty uses

machine learning, anomaly detection, and integrated threat intelligence to identify and prioritize potential threats. Guard Duty analyses tens of billions of events across multiple AWS data sources, such as AWS CloudTrail, Amazon VPC Flow Logs, and DNS logs. With a few clicks in the AWS Management Console, Guard Duty can be enabled with no software or hardware to deploy or maintain. By integrating with AWS Cloud Watch Events [?], Guard Duty alerts are actionable, easy to aggregate across multiple accounts, and straightforward to push into existing event management and workflow systems.

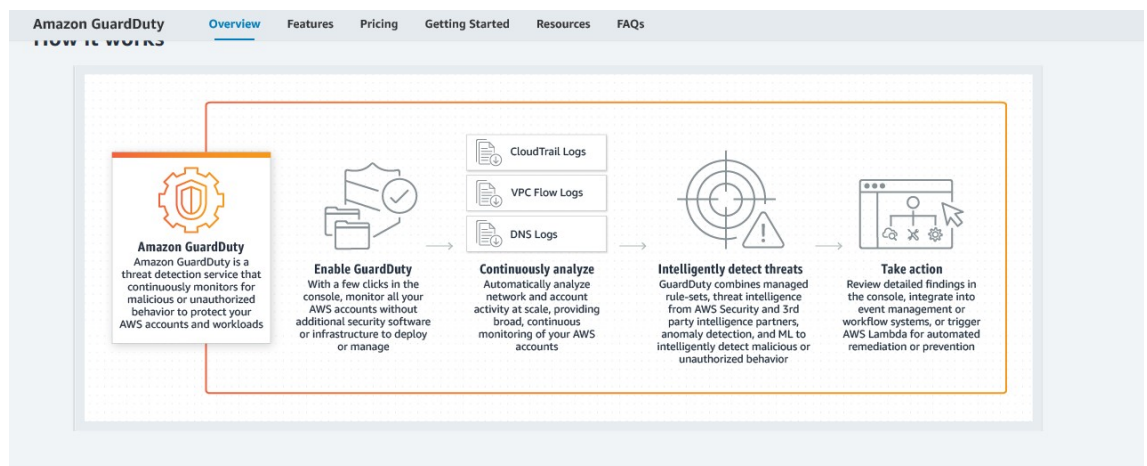


Figure 3.2: Amazon Guard Duty [?]

3.5 How Google finds anomalies in GCP cloud

Google uses an open source library Forseti [?] which can

1. Detect unusual firewall behaviors between snapshots.
2. Alert users to any unusual behaviors and provide a comparison with expected behaviors.
3. Provide potential remediation steps.

The key elements for this technology are firewall rules. Firewall rules can be inbound or outbound. A firewall rule can either allow traffic based on IP address or ports. Firewall rules are applied to those instances which are associated with the user who has created his cloud in GCP setup. The figure below shows the technical architecture as how this has been implemented in GCP

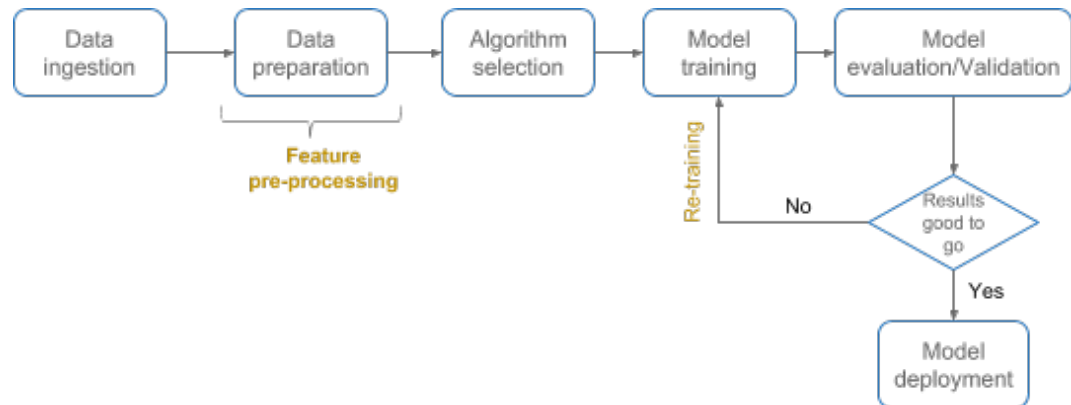


Figure 3.3: GCP Anomaly Detection [?]

3.6 Finding Anomaly in Cloud

The main goal of an anomaly detection system is to discriminate the occurrence of hostile activities from the normal events, and such analysis must be accomplished in a sufficiently flexible and effective way to keep up with the continuously evolving world of cyber security where new, previously unknown, anomalies can continuously emerge over time. In doing this, it must either try to model any kind of attack or anomalous event that can affect the network (there are thousands of known ones) or simply construct a sufficiently general model describing the normal traffic. Such model is usually built on the basis of training data, and used in classifying previously unseen or suspicious events. Classification is the fundamental task in unattended detection, by which the system “learns” to automatically recognize complex traffic patterns, to distinguish between different events based on the corresponding patterns, and to make “intelligent” decisions. Specific machine learning techniques, such as Neural Networks or Support Vector Machines are used in an anomaly detection system.

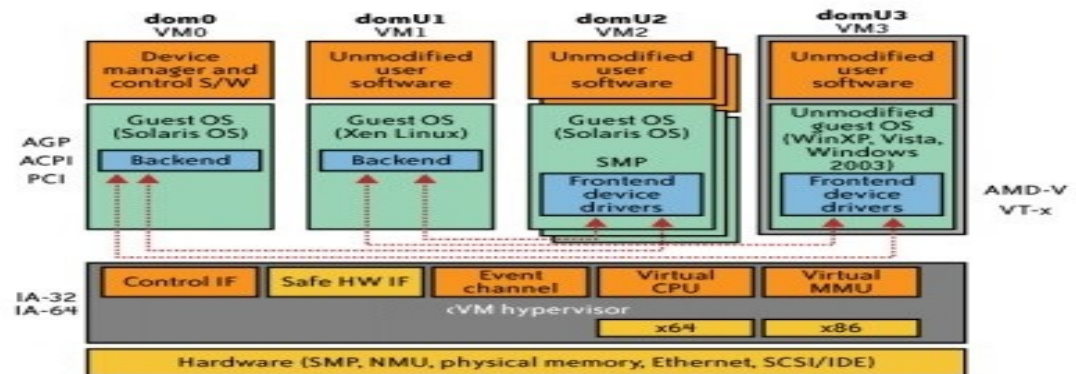


Figure 3.4: Hypervisor working [?]

3.6.1 Building the Anomaly Detection System

An Anomaly Detection System can be build using a generalization capability from training data which is needed to correctly classify future data as normal or abnormal. These resulting approaches can be categorized as generative or discriminating. A generative approach builds a model solely based on normal training examples and evaluates each testing case to see how well it fits the model. A discriminating approach, on the other hand, attempts to learn the distinction between the normal and abnormal classes. Thus, based on the characteristics of training data used to build the model, anomaly detection can be divided into three broad classes which appear below the table (See Table 3.1).

Technique	Category
Supervised anomaly detection	A
Semi Supervised Anomaly Detection	B
Unsupervised anomaly detection	C

Table 3.1: Type of anomaly detection techniques.

3.7 Detecting the deviation

In particular, in the context of abuse and network intrusion detection [?], the interesting objects are often not rare objects, but unexpected bursts in activity. This pattern does not adhere to the

common statistical definition of an outlier as a rare object, and many outlier detection methods (in particular unsupervised methods) will fail on such data, unless it has been aggregated appropriately. Instead, a cluster analysis algorithm may be able to detect the micro clusters formed by these patterns. Three broad categories of anomaly detection techniques exist, i.e. Statistical Anomaly Detection Systems, Data Mining Based Anomaly Detection Systems, Machine Learning Based Anomaly Detection Systems. [?] Unsupervised anomaly detection techniques detect anomalies in an unlabeled test data set under the assumption that the majority of the instances in the data set are normal by looking for instances that seem to fit least to the remainder of the data set. Supervised anomaly detection techniques require a data set that has been labeled as "normal" and "abnormal" and involves training a classifier (the key difference to many other statistical classification problems is the inherent unbalanced nature of outlier detection). Semi-supervised anomaly detection techniques construct a model representing normal behavior from a given normal training data set, and then test the likelihood of a test instance to be generated by the learned model.

Anomaly detection [?] finds its use in a lot of fields such as fraud detection, fault detection, health monitoring, intrusion detection, event detection in sensor networks, finding disturbances in ecosystem. It is often used in pre processing to remove anomalous data from the dataset. In supervised learning, removing the anomalous data from the dataset often results in a statistically significant increase in accuracy. Several anomaly detection techniques have been proposed in literature.

Some of the popular techniques are:

- Density-based techniques (k-nearest neighbor, local outlier factor, isolation forests, and many more variations of this concept).
- Subspace-, correlation-based and tensor-based outlier detection for high-dimensional data.
- One-class support vector machines.
- Replicator neural networks, auto encoders, long short-term memory neural networks
- Bayesian Networks. Hidden Markov models (HMMs).
- Cluster analysis-based outlier detection.
- Deviations from association rules and frequent item sets.
- Fuzzy logic-based outlier detection. [?]
- Ensemble techniques, using feature bagging, score normalization and different sources of diversity.

Different methods perform differently a lot on the data set and parameters, and methods it may have little systematic advantages over another when compared across many data sets

and parameters. Sample Anomaly Detection Problems. These examples show how anomaly detection might be used to find outliers in the training data or to score new, single-class data. Algorithm for Anomaly Detection. Oracle Data Mining supports One-Class Support Vector Machine (SVM) [?]for anomaly detection. When used for anomaly detection, SVM classification does not use a target. Capgemini uses an anomaly detection solution powered by Google Cloud Platform [?] which makes it possible to find out threat due to presence of malicious users in advance. With a combination of existing rules-based model and advanced unsupervised machine learning capabilities this is achieved. And provide clients with a more robust and comprehensive solution to track anomalies in run time.

3.8 Building a classifier

The success of a classifier meant to be used in practice depends ultimately on its ability to perform well not only with the data used for its testing, but most of all with real-world data. Although a methodologically sound procedure ensures that the classifier is tested against data it has never seen before (i.e., in the training phase), there is no guarantee whatsoever that testing data will be representative of, and resemble closely, real-world data. Such data surely are not available at the time of testing. On the other hand, when using a portion of the training data as a validation dataset to verify and refine the selection of model hyper-parameters, training data could “leak” some information about the validation conditions if the partitioning of data into training and validation sets is not done properly so as to ensure that instances relative to the same (or very close) conditions go in the same part. Connections recorded with the same conditions might, in fact, share some. Because attacks often occur across different tenants, various anomaly detection techniques can combine AI algorithms to analyze attack sequences that are reported on each subscription. These techniques identify the attack sequences as well as prevalent alert patterns, instead of just being incidentally associated with each other.

Chapter 4

Second Contribution

We have used KDD cup data set to implement the algorithms for anomaly detection and find vulnerabilities in cloud system. The python packages used to implement this are following

- numpy
- pandas
- scikit-learn
- matplotlib

We started by working on a reduced data set (the 10 percent dataset later). The module numpy allows them to perform high levels of computation to other modules. Pandas module helps to read data files of various formats in order to store them as data frame objects, and it is a popular framework for data science in general. These data frames hold data entries in a fashion a similar to arrays and can be thought of as a table of values. Matplotlib is a Python library that allows us to plot data. Finally, scikit-learn is a package that allows us to apply various machine learning models to data sets as well as it provides tools for data analysis. A tool called Anaconda Navigator was used to implement this.

4.0.1 Data Description

Data Files: Description of files used from data set

kddcup.name A list of features.

kddcup.data.gz The full data set (743 mb uncompressed)

kddcup.data_10percent.gz A 10% subset of original dataset. Was used to train the classifiers.

kddcup.testdata.unlabeled_10_percent.gz corrected.gz Test data with corrected labels.
training_attack_types A list of intrusion types.

```
In [2]: import pandas
from time import time
col_names = ["duration", "protocol_type", "service", "flag", "src_bytes",
             "dst_bytes", "land", "wrong_fragment", "urgent", "hot", "num_failed_logins",
             "logged_in", "num_compromised", "root_shell", "su_attempted", "num_root",
             "num_file_creations", "num_shells", "num_access_files", "num_outbound_cmds",
             "is_host_login", "is_guest_login", "count", "srv_count", "error_rate",
             "srv_error_rate", "error_rate", "srv_error_rate", "same_srv_rate",
             "diff_srv_rate", "srv_diff_host_rate", "dst_host_count", "dst_host_srv_count",
             "dst_host_same_srv_rate", "dst_host_diff_srv_rate", "dst_host_same_src_port_rate",
             "dst_host_srv_diff_host_rate", "dst_host_error_rate", "dst_host_srv_error_rate",
             "dst_host_rerror_rate", "dst_host_srv_rerror_rate", "label"]
kdd_data_10percent = pandas.read_csv(r"C:\Users\tapas\data\IIITG Lab assignments\mtech project\code\edit-kdd-cup-99-spark-master\kdd_data_10percent.csv")
kdd_data_10percent.describe()
```

Figure 4.1: Initializing the dataset to feed in algorithm

Then the generated output which is generated by reading above variables.

```
Out[2]:
```

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logins	logged_in	num_c...
count	494021.000000	4.940210e+05	494021.000000	494021.000000	494021.000000	494021.000000	494021.000000	494021.000000	494021.000000	49
mean	47.979302	3.025610e+03	868.532425	0.000045	0.006433	0.000014	0.034519	0.000152	0.148247	
std	707.746472	9.882181e+05	33040.001252	0.006673	0.134805	0.005510	0.782103	0.015520	0.355345	
min	0.000000	0.000000e+00	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	4.500000e+01	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	5.200000e+02	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	1.032000e+03	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
max	58329.000000	6.933756e+08	5155468.000000	1.000000	3.000000	3.000000	30.000000	5.000000	1.000000	

8 rows x 38 columns

Figure 4.2: Output table generated after reading data

Now we have our data loaded into a “Pandas“ data frame. In order to get familiar with our data, let’s have a look at how the labels are distributed. `kdd_data_10percent['label'].value_counts()`
We get following attack types by reading the known attacks from the given dataset.

4.0.2 Feature selection

Initially, we will use all features. We need to do something with our categorical variables. For now, we will not include them in the training features. Classification is an important decision-making tools in data mining where the objective is to find some mechanism in order to get a near approximate answer for a particular problem. The answer may be a decision, predicting a behavior, the outcome of a process, or an information, which can act as an input to the next step . By finding an answer which is near to an approximate answer we can conclude that classification method normally gives a near optimal (based on the implementation) solution out of many possible solutions for a particular problem. Once the log files are of an appropriate

```

Out[3]: smurf.          280790
         neptune.       107201
         normal.        97278
         back.          2203
         satan.         1589
         ipsweep.       1247
         portsweep.     1040
         warezclient.   1020
         teardrop.      979
         pod.           264
         nmap.          231
         guess_passwd.  53
         buffer_overflow. 30
         land.          21
         warezmaster.   20
         imap.          12
         rootkit.       10
         loadmodule.    9
         ftp_write.     8
         multihop.      7
         phf.           4
         perl.          3
         spy.           2
         dtype: int64

```

Figure 4.3: Attack types

format, several statistics are calculated concerning them. Anomaly detection from KDD Data Set performed very well. The log files from different different operating systems create different kind of inconsistencies in the output. One problem is marking false positives in the data set.

Sklearn is a tool that helps dividing up the data into a test and a training set.

```

from sklearn.model_selection import train_test_split

features_train, features_test, labels_train, labels_test = train_test_s
features, labels,
test_size=0.20, random_state=42)

```

Once the data is separated into test and training sets, we can begin to choose a classifier.

```

# import
from sklearn.neighbors import KNeighborsClassifier

```

KNearestneighbor can use any of the following algorithms “auto“, “ball_tree“, “kd_tree“, “brute“, the default is “auto“. We can use any different classifier here other than RandomForestClassifier sklearn is a toolkit which has various algorithms implemented and any of them can be choosen to implement a classifier depending upon what you want to do following shows implementation of RandomForestClassifier.

```
# initialize
clf = RandomForestClassifier()

# train the classifier using the training data
clf.fit(features_train, labels_train)

# compute accuracy using test data
acc_test = clf.score(features_test, labels_test)

print ("Test Accuracy:", acc_test)
```

A classifier can fail to predict the correct result from a given data set if it encounters false positives, and false negatives. A false positive is where something is assumed to be true when it's really false. A false negative is where something is assumed to be false when it's really true. In such scenarios, precision and recall are used to describe the results mathematically rather than false positives and false negatives. Which are defined as Formally, precision and recall are calculated like so:

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \quad (4.1)$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \quad (4.2)$$

$$Accuracy(F1score) = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4.3)$$

Precision gives us a measure of how many type of positive classifications are correct where as recall gives us a measure of how correctly we have identified the anomaly.

Sklearn has builtin functions to calculate the precision and recall scores

```
from sklearn.metrics import recall_score, precision_score

precision = precision_score(labels_test, pred, average="weighted")
recall = recall_score(labels_test, pred, average="weighted")

print ("Precision:", precision) #
print ("Recall:", recall) #
```

To detect anomalies using SVM following is the required pseudo code for implementation, using sklearn's support vector classifier lines of code;

```
from sklearn.svm import SVC  
clf = SVC
```

The accuracy of detection and results is different for different algorithms and different approaches. Finally we can conclude that Attacks fall into four main categories:

- DOS: denial-of-service, e.g. syn flood;
- R2L: unauthorized access from a remote machine, e.g. guessing password;
- U2R: unauthorized access to local superuser (root) privileges, e.g., various “buffer overflow” attacks;
- probing: surveillance and other probing, e.g., port scanning.

Chapter 5

Conclusion

As we can see anomaly detection is an important topic for research. There is always a scope of improvement in existing methods. This work explored the topic from cloud computing perspective. When you have thousands of virtual machines running inside the data center of cloud service provider then there has to be some mechanism by which they can detect anomalies in their system. Implementation of each service provider would be different because they have different log files and different approaches for implementation. The accuracy of result depends upon the data available and more the system is subject to exposure more it gains intelligence. Existing work is just a small contribution in the field of anomaly detection and shows how anomaly detection techniques can be applied to detect anomalies in a cloud based scenario. Anomaly detection is about finding patterns that do not belong to what is a normal observation. It has its use in each domain of business not only in cloud computing. Using anomaly detection we can detect if a specific port or a service is having abnormal transactions. This kind of information which is available in log files can give vital clue to cyber experts. Anomaly detection is an alternative approach than a traditional intrusion detection system.

Author's Biography

Tapas received his B. Tech & MBA dual degree in Information Technology from ABV-IIITM, in 2009. He has been pursuing M. Tech at the Department of Computer Science and Engineering, IIIT Guwahati, since July 2018.