

# Reveal Deceit Entrance in the Cloud Computing Environment

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## ABSTRACT

Paper states a strategy for detecting doubtful access to the cloud infrastructure. Collaborative filtering algorithm methods have been implemented to detect such doubtful access. The normal behavior of the user is formed in the shape of a cloud model, and these models is compared with each other by using the cosine similarity method and by applying the collaborative filtering method we try and find the deviations are evaluated as compare the normal usual behavior. If the deviated result is above than the threshold, the user who gained access to the system can be remarked as doubtful.

**Keywords:** Cloud Computing; Masquerade Attack; Collaborative Filtering

## I. INTRODUCTION

Cloud technologies have significantly changed the way we store and access our personal and business information. New security threats and problems emerged with this new computing and communication paradigms based on these technologies. Compared to the old traditional technologies the nature of the threats brought by the cloud technologies to the organization infrastructure has changed. The Cloud Security Alliance - CSA, which is actively operating in the area of the standardization of the security issues of cloud technologies classifies the main threats brought by this technology as follows:

**Threat 1:** Abuse and Nefarious Use of Cloud Computing

**Threat 2:** Insecure Interfaces and APIs

**Threat 3:** Malicious Insiders

**Threat 4:** Shared Technology Issues

**Threat 5:** Data Loss or Leakage

**Threat 6:** Account or Service Hijacking

**Threat 7:** Unknown Risk Profile

SPI – Service Platform Infrastructure model can be implemented for threat number 1<sup>st</sup> and 3<sup>rd</sup> in each layer. In both of these threats in order to use the resources illegally the attacker tries to present himself to the system as a legitimate user by capturing legitimate user's identity information. In the literature source these threats are known as masquerade attacks. According to the cybercrime watch survey conducted by the organization CERT in 2010, the first place among the top 5 electronic crimes belongs to viruses, worms and other malicious codes, the second part takes the unauthorized access.

A hacker from France is a good example of this threat. The Twitter incident committed by the French hacker can be introduced as an example of this type of attacks. Several Twitters corporate and personal documents were leaked to the technological website called The Tech-Crunch and customer accounts including the account of the US President Barack Obama were illegally accessed. These french attacker used a Twitter administrator password in order to gain access to Twitters corporate documents hosted on Google infrastructure as Google Docs. The damage was significant both for Twitter and for its customers.

Various researches work and under process to discover this kind of masquerade attacks. In one of these studies in order to discover the masqueraders a new approach has been presented. This approach implements the comparison between the two users command sequence. This method is based on the similarity measured between the 10 most recent commands and a user profile. But this approach is not suitable for cloud infrastructure because cloud systems are heterogeneous systems. Here the virtual machines which form cloud systems are execute under the different operating systems like Windows, Linux, UNIX, Network. It is also likely that different commands are used for the same operation. For this reason, it is impossible to evaluate similar users by their command sequence.

A sequence alignment method, which is broadly used in bioinformatics, is applied to discover the illegal accesses. As it can be seen most of the studies are focused on the detection of unusual or variable command sequence applied by the users. The legitimate users of the computer system are familiar with the files on that system and are aware of their location of the files. Any search for the specific files is likely to be targeted and limited here. A masquerader, however, who gets access to the victim's system illegitimately, is unlikely to be familiar with the structure and the contents of the file system. For this, his search is likely to be widespread and untargeted as well as the type and sequence of commands applied by the users in the system are being different. Taking this into account, the user profile reflecting his search behavior is created at and the one-class modeling technique is developed in order to detect the illegal intrusion.

However it should be noted that, when the attacker is being more deeply familiar with the genuine user behavior he can more accurately imitate him in the system. In this case, the above mentioned methods lose their influence and the detection of the illegal accesses by that way does not allow obtaining good results. Typically, a user who gains access to the

cloud system by masquerading under the genuine user always has a unique interest on the selected target resources. In this case the detection of the illegal accesses by modeling the user's specific interest may allow obtaining significant results.

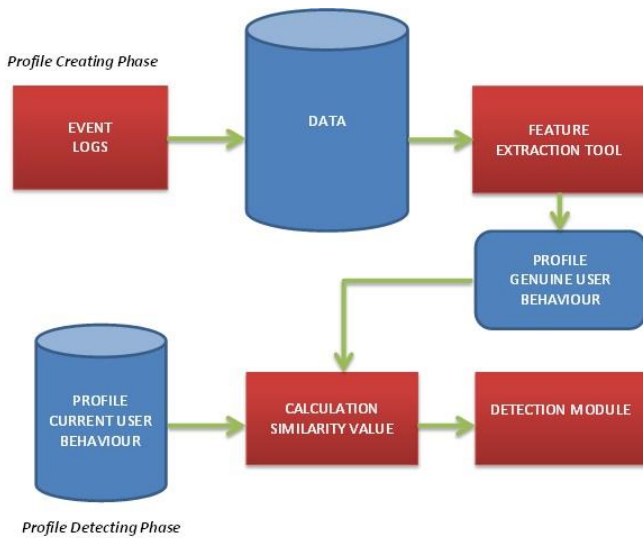
This paper creates a profile which reflects the interest behavior of each user and this profile is considered as a cloud model. This cloud model not only reflects command sequence used by the user but also the statistical characteristics of the operations conducted by the users. According to this method, in order to discover the illegal attack the normal behavior of a user is modeled as a cloud model first; then these models are compared and the deviations from this behavior are evaluated. If the deviation value becomes above the threshold the user who gained access to the system is evaluated as the illegal user.

## II. RESULTS AND DISCUSSION

The unauthorized access or attacks or access using a fake identity in order to access the files or information of a person or organization can be called as Masquerade attack, this attacker or hacker act and makes the system think as if it is legitimate access identification. The most common information which can be used to detect the masquerade attacks is contained within the actions the masquerader performs. This set of actions is known as a behavioral profile. The masquerade detection techniques are based on the premise that when a masquerader attacks the system he will sufficiently deviate from the legal user behavior. In other words, at first the normal behavior of the user is modeled as a profile, then this profile is compared with his current behavior and the obtained deviation cases are compared with normal profile for considering a masquerader attacks.

In this paper we propose a new approach for detecting a masquerader in the cloud environment. This approach is schematically described in following figure.

### III. USER PROFILE GENERATION



The above architecture for the masquerade detection is implemented in two phases:

#### 1) Profile creating phase.

The genuine user data is collected and on the basis of the collected information a behavioral profile is created for each user. This phase consists of two components. The Event logs implements the collection of the information on all events during the session. The Feature Extraction Tool generates the feature vector based on cloud model for the user.

#### 2) Detection phase.

The new user profile generating on the basis of the new user records and compared with the genuine user profile. There similarity value calculation block for each input vector there calculates the cosine similarity value. The similarity value here varies between 0 and 1.

After comparison if the similarity value is high, then the input data become very close to the user profile and if it becomes very low, then it is estimated as very different. According to the input data, the detection module classifies all users as genuine or imposter. Filtering formula calculates the deviation value and on the basis of the accepted threshold value in the system it makes a decision determining the user as genuine or imposter.

In order to recognize the anomalous behavior for this detection system, it forms a user profile to characterize a normal behavior. In this section we will describe the model underlying our approach to the user profiling and will discuss the implementation details of how profiles are formed from the user interest data.

#### A. Data Collection

The detection of the masquerade attacks is carried out on the basis of operations performed by the masqueraders in the system. This set of operations forms a user behavior profile. Based on these real data, it is possible to construct the interest profile in terms of the cloud model. This interest profile also can be called the feature vector of the user.

#### B. Feature Vector Construction

Users action is recorded as a score and is regarded as a drop of interest cloud, but the score value of all operations is regarded as an interest cloud. The cloud uses expectation  $E_x$ , entropy  $E_n$  and excess entropy  $H_e$  to represent one digital value. Together these three digital characteristics of  $i^{th}$  user interest cloud form the  $c_i$  characteristic cloud vector. While computing the similarity between users  $i$  and  $j$  we can judge from similarity between vector  $c_i$  and  $c_j$ . The key innovation there is getting characteristic vector  $c$  of the user interest cloud.

Assume that matrix  $A(u_j, n_i)$  represents the score data set of operations used by the users. Here,  $u_j$  implies the users,  $n_i$  the operations used by the users,  $Score_{i,j}$ , the score value of the  $i^{th}$  operation used by the  $j^{th}$  user. This assumption can be represented as follows in figure.

	$n_1$	$n_2$	...
$u_j$			
$u_1$			
$u_2$	$Score_{i,j}$		
$\vdots$			

6) The calculation of the entropy

$$E_n = \sqrt{\frac{\pi}{2}} \times \frac{1}{n} \sum_{k=1}^n |x_k - E_x| \quad \dots(6)$$

In order to get the cloud feature vector  $c=(E_x, E_n, H_e)$  of the user we need a backward cloud generator. Assume that a set of score values used operations denoted as  $X_k, k=(1,2,3,\dots, n)$ . Then an algorithm to determine the digital value  $(E_x, E_n, H_e)$  can be constructed as follows:

Input: a set of score values of operations  $X_k, k = \{1,2,\dots,n\}$

Output:  $(E_x, E_n, H_e)$  numerical characteristics

1) The calculation of the average  $X$  score value, according to score value of the number of  $X$   $k$  operations applied by the user

$$\bar{X} = \frac{1}{n} \sum_{k=1}^n x_k \quad \dots(1)$$

2) Absolute central moment calculation

$$M = \frac{1}{n} \sum_{k=1}^n |x_k - \bar{X}| \quad \dots(2)$$

3) The calculation of the variance of the event

$$S^2 = \frac{1}{n-1} \sum_{k=1}^n (x_k - \bar{X})^2 \quad \dots(3)$$

4) The calculation of the mean operation value

$$E_x = \bar{X} \quad \dots(4)$$

5) The calculation of the dispersion of operations

$$H_e = \sqrt{S^2 - E_n^2} \quad \dots(5)$$

In this work the characteristic vector  $c=(E_x, E_n, H_e)$  of the user cloud is determined by the above mentioned algorithm.

#### IV. DETECTING ANOMALOUS BEHAVIOR

For the detection of the anomalous behavior in the cloud infrastructure first of all let us provide comparison of the cloud vectors. Let the vector  $c=(E_x, E_n, H_e)$  present the cloud of  $i^{\text{th}}$  user, then the similarity between the  $i^{\text{th}}$  and the  $j^{\text{th}}$  users is labeled as  $\text{sim}(i, j)$  and is calculated as follows:

$$\text{sim}(i, j) = \cos(c_i, c_j) = \frac{c_i \cdot c_j}{\|c_i\| \cdot \|c_j\|}$$

where  $c_i=(E_{xi}, E_{ni}, H_{ei})$  and  $c_j=(E_{xj}, E_{nj}, H_{ej})$

After the calculation of the similarity measure the detection module as shown in the above figure of masquerade attack detection system, classifies the input vector and identifies the access as normal or anomalous. For the implementation of this process the following method is proposed.

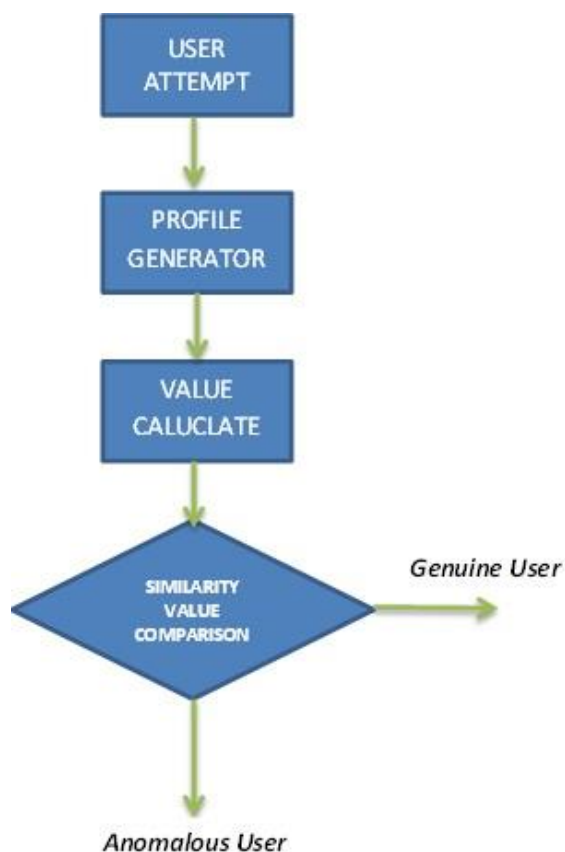
#### V. CLASSIFYING USER BEHAVIOR

The input data of the user and his recorded profile may also have some deviation cases can be taken place. In order to accept the decision about normal or anomalous accesses it is necessary to calculate the degree of this deviation value. This deviation value can be calculated via following filtration formula:

$$D_{i,j} = \frac{\sum_{j \in N} (S_{i,j} \times \text{Score}_{i,j})}{\sum_{j \in N} (|S_{i,j}|)}$$

Here  $S_{ij}$  is a weight ratio, which represents the similarity value between the  $i^{\text{th}}$  and the  $j^{\text{th}}$  users;  $\text{Score } S_{ij}$  —is a score value of the  $i^{\text{th}}$  operation used

by the  $j^{\text{th}}$  user. The classification of the users here fulfilled on the basis of the threshold value accepted in the system. If  $D_{i,j}$  becomes less than the threshold value, then the system evaluates the user as genuine, otherwise he is evaluated as anomalous. The operation flow figure as shown below, covers the above cases can be constructed as follows:



## VI. EXISTING MASQUERADE DATASETS

There are numbers of datasets which enable to evaluate the performance of the 988asquerade attack detection techniques. Most papers about the 988asquerade detection use this SEA dataset with its associated configuration. The SEA consists of the commands collected from the UNIX account audit data. Among all fields of audit data provided by account only the username and the command were taken. The data describe 50 different users each issuing 15,000 commands. The first 5000 commands are considered as genuine. The remaining 10,000 commands of each user are divided into 100 blocks consisting of 100 commands each.

Another dataset is called Greenberg dataset which contains the data from 168 UNIX users. Users are classified into four groups: novice programmers, experienced programmers, computer scientists and non-programmers. The data are stored in the plain text files that record the following information: the session start and end times, the command line as entered by the user, the current working directory, any alias expansion of the previous command, an indication whether the line entered has a history expansion or not, and any error detected in the command line.

PU or Purdue University dataset or just dataset consists of the UNIX command histories of 4 users of the Purdue Millennium Lab, collected in four months. A few works use this dataset and this may be due to its low number of users.

RUU dataset. This dataset was collected by Columbia IDS group and consists of Windows commands. The dataset was collected from 34 normal volunteer users and 14 masquerade users. They model how normal users typically search a file system and use these models to detect the unusual searches that may be considered as masquerades. The dataset includes the records of the search conducted by the 988asquerade who should perform a specific task to find any data useful for his financial gain on a previously unknown file system within 15 minutes.

This datasets suffer partially or fully from the several deficiencies which prevent their adoption for the cloud environments. In this perspective, their most significant weakness is the lack of real masquerade data. No command sequence was issued by the attackers, only the RUU dataset includes the real masquerades but they are predefined limited scenario. The main shortcomings of these datasets are:

- ✓ The cloud systems are heterogeneous and the user audits may be distributed among various

machines running distinct operating system like windows, linux or others.

- ✓ The absence of the command arguments and other useful details such as when the user commands were issued, the duration of each user session and the type of operations implemented by the users in the system.
- ✓ They are not suitable for training or testing any cloud detection systems because of their small size.
- ✓ Any efficient Cloud dataset should coverage for attacks in all cloud service models (SaaS, PaaS, and IaaS).

At present, there is no standard dataset allowing testing the masquerade attacks detection techniques in the cloud infrastructure. This relates to a necessity of special tools for the access of the cloud infrastructure, a necessity of special permissions, with distributions of audit data across different environments e.g. Windows, Linux, and network, with necessity of a huge size of the audit data for cloud systems more than 20 GB. At feature it would be significant to provide investigations in this area to create such datasets.

## VII. CONCLUSION

In this paper, for the detection of the masquerade attacks in the cloud infrastructure collaborative filtering algorithm based on the cloud model is proposed. One of the advantages of this model is the identification of the similarity between the users on the basis of the cloud model. While using the similarity measurement method based on the cloud model, it does not require a strict comparison between the score value of operations used by different users. Here we provide the calculation of the statistic features of the score values of all operations used by the user at the access point, then we provide a comparison of statistics features of the input data and based on these we determine the similarity between the input data.

## VIII. FUTURE WORK

Future work will focused on providing experiments to prove the effectiveness of implementation of collaborative filtering algorithm constructed on the cloud model onto illegal access detection problem in the cloud computing environment.

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