Arhuaco: Deep Learning and Isolation Based Security for Distributed High-Throughput Computing

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Abstract Grid computing systems require innovative methods and tools to identify cybersecurity incidents and perform autonomous actions i.e. without administrator intervention. They also require methods to isolate and trace job payload activity in order to protect users and find evidence of malicious behavior. We introduce an integrated approach of security monitoring via Security by Isolation with Linux Containers and Deep Learning methods for the analysis of real time data in Grid jobs running inside virtualized High-Throughput Computing infrastructure in order to detect and prevent intrusions. A dataset for malware detection in Grid computing is described. We show in addition the utilization of generative methods with Recurrent Neural Networks to improve the collected dataset. We present Arhuaco, a prototype implementation of the proposed methods. We empirically study the performance of our technique. The results show that Arhuaco outperforms other methods used in Intrusion Detection Systems for Grid Computing. The study is carried out in the ALICE Collaboration Grid, part of the Worldwide LHC Computing Grid.

Keywords Grid Computing Security · Intrusion Detection and Prevention · Deep Learning · WLCG · Isolation · Malware Detection

1 Introduction

The Worldwide LHC Computing Grid (WLCG) is one the most remarkable examples of High-Troughput Computing (HTC) distributed infrastructure for scientific applications. The WLCG is the global Grid that analyzes data from the Large Hadron Collider (LHC) at CERN, with 170 sites in 40 countries. Due to their size, complexity, reputation and required access by Internet these systems are continuously exposed to attackers. Authenticated users have the freedom to execute arbitrary code and to transfer arbitrary data that is required for their experiments. External or insider attackers may take advantage of the Grid functionality to carry out unauthorized activities such as running malware or mining cryptocurrencies. The Grid is a heterogeneous and dynamic environment where it is difficult to adapt traditional rule based Intrusion Detection Systems (IDS).

The distributed usage of High-throughput Computing (HTC) farms for data processing tasks - known as Grid Computing - has been very successful in High Energy Physics (HEP), weather forecasting, brain research and astronomy research, just to mention a few examples. Scientists can submit jobs composed of custom code and experimental data. The computing Grid has been envisioned as an analogy for the electrical Grid, for computing resources on demand. The Worldwide LHC Computing Grid (WLCG) enables the scientists to analyze massive amounts of physics data and it allowed for the experimental validation of the existence of the Higgs boson [10]. The WLCG integrates computer centers worldwide that provide computing and storage resource into a single infrastructure accessible by all Large Hadron Collider (LHC) physicists. Currently, it combines the power of nearly 170 sites in 40 countries, connected with 10-100 Gb links, with more than 600,000 processing cores and 700 PB of storage capacity. It is capable of processing more than 2 million jobs per day. The ALICE (A Large Ion Collider Experiment) Collaboration has built a dedicated detector to exploit the unique physics potential of nucleus-nucleus collisions at LHC energies. Its aim is to study the physics of strongly interacting matter at the highest energy densities reached so far in the laboratory [12]. As a mem-
ber of the WLCG, the ALICE experiment has developed the ALICE production environment (AliEn) [3], implementing many components of the Grid computing technologies that are needed to store, process and analyze the collected data. Through AliEn, the computing centers that provide CPU and storage resources for ALICE can be seen and used as a single entity - any available node executes jobs and file access is transparent to the user, wherever in the world a file might be located. Figure 1 represents the flow of data in the WLCG.

Authorized users of Grid computing systems have the freedom to carry out research on experimental data. They are able to execute arbitrary code and transfer any required data. This means that potential insider attackers have the same capabilities. The focus of this study is on the security issues related to the Grid job execution environment inside site worker nodes. Frequently in HEP Grids [5], the jobs running in the worker nodes have access rights that are beyond of what is actually required, restricted only by one or several local Linux accounts. When multiple jobs are executed with the same account, an attacker with control over one job could tamper another user jobs, blaming the owner of any malicious activity. These processes could also have access to sensitive server data and restricted networks. Therefore, Security by Isolation (SbI) mechanisms for processes and networks are important requirements for Grid computing.

An insider attacker may misuse the power of the Grid for activities not related to physics data analysis. Complex HTC infrastructure such as the WLCG are attractive targets for external attackers as well. An attacker might take advantage of the Grid functionality to tamper with user jobs, escalate privileges, access sensitive server configuration data, setup a Denial of Service (DoS) attack or mine cryptocoins, to name a few of the possibilities. This could be accomplished by exploiting unknown or unfixed software or hardware vulnerabilities, listen to user network traffic to gather sensitive clear text information or by guessing weak user credentials among other possibilities. Millions of jobs might be running in Grids like the WLCG every day. The user’s ability to run arbitrary code and the lack of proper isolation make detecting intrusions a more challenging task than in other systems. Traditional Intrusion Detection Systems (IDS) require rules written by security professionals. Those rules need to be updated constantly which requires an important amount of effort. Rule based IDS are difficult to adapt to very dynamic environments such as the Grid [18]. Machine Learning algorithms can help to automate the way IDS are built and updated, by using security monitoring data collected from the protected systems [60]. In the Grid, the amount of this monitoring data is huge due to the number of running jobs. Deep Learning methods may help to analyze this data to improve the IDS detection accuracy.

We introduce Arhuaco, a framework that adopts Linux Container (LC) technology to provide SbI and security monitoring by applying Deep Learning for detection and prevention of abnormal activities based on multiple sources of monitoring data such as network connections and system calls. Arhuaco gives researchers the ability to generate complementary training data by a Recurrent Neural Network. This can be used to improve the detection performance and adapt the detector to new environments. A dataset for Machine Learning (ML) training of malware detection on Linux based Grid computing is described. Some of the most popular Grid systems are just starting to explore the usage of SbI and IDS for security monitoring [65]. As we describe in the related work section there are no studies that leverage the capabilities of Linux Container isolation and monitoring in combination with Deep Learning and data generation for Intrusion Detection. We also show in the next section that there is no tool implementing the mentioned techniques for Grid job payload monitoring in order to detect intrusions. We describe the design, implementation decisions and tests of our proposed methods in the ALICE Collaboration Grid, part of the WLCG. We demonstrate that the selected algorithms and techniques outperform other methods used on IDS for Grid Computing.

This document is organized as follows. Section 2 presents the state of the art on ML and isolation based security methods applied to distributed environments especially in Grid computing. Section 3 provides background information on the SbI approach and an overview of the classification task in Machine Learning and generative models. Section 4 and 5 describe the Arhuaco design and implementation based on our ideas. Section 6 shows the results obtained from testing our approach. Finally section 7 and 8 summarize our findings and indicate directions of our future research.
2 Related work

2.1 Security by Isolation in Grid Computing

Virtual Machines (VM) have been suggested many times to solve the isolation problems in Grid computing [20]. VMs are emulated machines with their own kernel while Linux Containers (LC) can share a single kernel. Several researchers - [18] and [17] - have proposed the usage of LCs to provide a level of isolation between the Grid jobs and the underlying system and network. Saving system resources in High-throughput Computing (HTC) applications is critical, and LC help to reduce the overall performance impact. [67] presents a comparison of the performance of several virtualization technologies including VM, and shows that container based systems have a near-native performance of CPU, memory, disk and network. [49] analyzes LCs and VMs and finds similar results in terms of performance and scalability. [7] shows a success real experience for LCs providing isolation in a Grid site at the ALICE High Level Trigger (HLT). Our study further extends this direction. In particular, we are interested in how this isolation mechanism can be integrated with a security monitoring system, that provides methods to enforce Intrusion Prevention and Detection in Grid computing.

2.2 Intrusion Detection

In [29] an extensive review of Intrusion Detection Systems is presented. Intrusion is defined as the attempt to compromise confidentiality, integrity and availability and Intrusion Detection as the process of monitoring the events occurring in a computer system or network, and analyzing them for signs of intrusions. The cited study presents several open source technologies as the most used solutions for IDS such as SNORT [44] and OSSEC [21]. False positive and false negative are two very common metrics to assess the degree of accuracy. Relevant features can be sets of audit trails (e.g. system logs, system commands) on a host, network packets or connections, wireless network traffic and application logs.

Machine Learning has been proposed in many studies to improve IDS. [60] summarizes the state of the art on ML techniques applied to Intrusion Detection and prevention. It states that the most commonly used techniques in the topic have been K-nearest neighbor (K-NN), Support Vector Machines (SVM), Artificial Neural Networks, self-organizing maps, decision trees, Naïve Bayes networks, genetic algorithms and fuzzy logic for one single classifier approaches. On the other hand for hybrid classifiers, using several classifiers, neuro-fuzzy techniques, clustering-based approaches have been used especially for parameter tuning and classification. Single classifiers with K-NN and SVM are very popular, mainly the second one. For hybrid approaches an integrated framework, where a method is used for feature selection while another method is used for classification is common. KDD99 [45] is presented as the standard database for testing ML based IDS. [66] shows an overview on the usage of computational intelligence research on IDS. According to the review, misuse detection approach is widely adopted in the majority of commercial systems, because it is simple and effective, but it can not detect novel or targeted attacks. The other common method is anomaly detection. It extracts patterns from behavioral habits of end users, or usage history of networks and hosts. In the intrusion detection field, supervised learning usually produces classifiers for misuse detection from class labeled training datasets. Unsupervised learning satisfies the requirement of anomaly detection, hence it is usually employed in anomaly detection. The authors present two benchmarks, the DARPA-Lincoln datasets [31] and the KDD99 datasets [45] as the most utilized. According to their work, the most commonly used algorithms are Neural Networks like Feed forward Neural Networks, Radial basis function neural networks, Recurrent Neural Networks, Self-organizing maps and Adaptive resonance theory.

2.3 Methods used in Grid related Intrusion Detection

There are previously proposed methods for IDS in Grid computing. Some of them describe schemes that are not related to Machine Learning nor computational intelligence. For example [58] employs a relational grid monitoring architecture, [14] presents a bottleneck verification approach, [50] describes a streaming database approach, [61] utilizes gossip algorithms, [69] represents a multi-agent approach, and [34] introduces a web services correlation service. On the other hand, some articles are focused on ML topics such as [59], that adopts learning vector quantization Neural Networks, [47] and [62] utilize feed forward Neural Networks, [25] applies auto immune systems and [57] also makes use of learning vector quantization neural networks, all of them with a single classifier approach. [68] utilizes a hybrid approach, with a soft computing based self-organize map dimension reduction technique, a fuzzy Neural Network and a genetic algorithm.

None of the previously presented studies applies Security by Isolation to further improve security incident detection. Neither of them makes use of Deep Learning approaches that allow researchers processing huge real time streams of data produced in Grids like the WLCG. In addition, we could not find the usage of generative methods by Recurrent Neural Networks to improve the training datasets.
2.4 Grid IDS related datasets

Grid computing is a unique environment with special requirements. We analyze the behavior of the job payloads. Therefore, using standard datasets for ML based IDS could be ineffective. We could not find any available dataset for IDS training in Grid computing. However several studies describe custom metrics employed. In [58] and [50], the authors generate a dataset consisting of one or more log files. [14] uses an operating system kernel module to gather system calls. In [47] the measurements are extracted from audit data of low level IDS. To identify misuse committed by insider attackers, their system analyzes the behavior by resource usage data like CPU time and memory usage. The authors gather audit data from HIDS, also extracting operating system data throughout the grid middleware and the syslog protocol. In the implementation level they use OSSEC-HIDS and Snort. [61] uses Snort alerts as the input metrics by the intrusion detection exchange protocol. [25] proposes user-level data built from user ID, role, type and quantity of resources being consumed, and system-level data is composed of CPU usage rate, states of main and the secondary memory and attributes of system files. The identification, type, priority, status of processes and the states of CPU when they are running are organized into process-level data. IP address and port number of source and destination, type of protocol, flags are grouped into network-level data. [69] analyses the network log data of its own monitoring area. In [68] the extracted features are system calls (ID, return value, return status), process (ID, IPC ID, IPC permission, exit value, exit status) and file access (mode, path, file system, file name, argument length). The extracted information is normalized between 0 and 1 for the input of SOM. [57] describes a method using generated log files as a host based intrusion detection. None of the mentioned datasets was made publicly available for other researchers, therefore we decided to collect our own dataset.

2.5 Malware Detection

The focus of this study is to run Grid jobs securely and analyze the payloads behavior in order to detect intrusions. Therefore, we use Linux malware samples to test our environment and collect a dataset of malicious data. This is a more practical approach than creating our own set of binaries with a limited set of malicious characteristics. There are several web sites that collect malware samples and make them available for the research community such as [63] and [64]. In the same direction [42] and [43] explore Machine Learning for malware classification, using system calls as main features for their classifier. [15] explores the usage of Deep Learning for static analysis of malware samples for classification. We use a similar approach, however, our goal is to provide real time misbehave detection in Grid computing, by analyzing huge flows of data that can be generated by the millions of jobs running in the Grid.

3 Background

3.1 Security by Isolation

Security by Isolation is a technique that enforces component separation (hardware or software) in a way that if one of them is compromised by an attacker, other components still remain safe [30]. There are several implementations providing SbI such as Virtual Machines, Linux containers and the Unix multiuser scheme. There are even security focused Operation Systems [48] built with SbI as one of their core features such as [54], [37] and [51].

3.2 Linux Containers

An LC is a set of processes running on top of a shared kernel [67]. They are isolated from the rest of the machine and can not affect the host or other containers, with the exception of exploitable vulnerabilities in the kernel or the container engine. It takes advantage of namespaces to have a private view of the system (network interfaces, PID tree, mount points). Cgroups are also applied to have a limited assignment of resources. LC can be seen as an extension of the virtual memory space concept to a wide system scope. They provide a set of features that have advantages over other virtualization technologies. They are lightweight, fast on booting, have a small memory footprint, and close to bare metal performance. Figure 2 describes a set containers working together, isolated and sharing the same kernel. In opposition, Virtual Machines have several kernels on top of a hypervisor.

![Fig. 2 Linux Containers on top of a common kernel](image)
3.3 Machine Learning for data classification

ML is a form of applied mathematics [19] that tries to model how human intelligence works. One of its common applications is the statistic estimation of complicated functions. ML is frequently applied in automatic classification of complex data, a task that traditionally has been carried out by human operators. We can define classification in ML as follows: the input data $x$ is a vector of $d$ elements $x = (x_1, ..., x_d) \in \mathbb{R}^d$ called a feature vector. To classify the input $x$ means to evaluate a classification function $C_W : \mathbb{R}^d \mapsto \{c_1, ..., c_k\}$ on $x$. The output is $C_W(x) = k^*$, where $k^* \in \{1, ..., k\}$; $c_k$ is the class to which $x$ corresponds, based on the model $W$ [9]. Different ML algorithms use different ways to find the model $W$. We can assume a simple two classes decision problem, defined as:

$$C(x) = W^T \phi(x) + b,$$

where $b$ is a bias parameter and $\phi(x)$ is a feature-space transformation. The training dataset corresponds to $N$ input vectors $x^1, ..., x^N$, with target values $c_1, ..., c_k$ where

$$c_n \in \{\text{normal, malicious}\}.$$  

The objective is normally defined as a loss function $\mathcal{L}$ that represents the penalty for mismatching the training data. The loss $\mathcal{L}(W)$ on parameters $W$ is the average of the loss over the training examples $x^1, ..., x^N$, as:

$$\mathcal{L}(W) = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}(W, x^i).$$

Training consists of finding the parameters $W$ that result in an acceptably small loss, in the best case the smallest one (global minimum).

3.4 Support Vector Machines (SVM)

SVM are very popular for automated classification in Intrusion Detection Systems [60]. We use them to compare the classification performance of our proposed Convolutional Neural Networks. SVM use hyperplane decision classifiers in a similar way to traditional perceptrons. However, the optimization objective is to maximize the margin, defined as the distance between the decision boundary and the training data that are closest to that hyperplane [39]. For Support Vector Machines the model $W$ is made of $k$ vectors in $\mathbb{R}^d$ where $W = \{w_i\}_{i=1}^k$. Here our objective is to optimize the parameters $W$ and $b$ such as:

$$c_n(W^T \phi(x^n) + b) \geq 1, n = 1, ..., N.$$  

The optimization problem can be expressed in a simpler way as:

$$\arg\min_{W, b} \frac{1}{2} ||W||^2.$$  

3.5 Deep Learning

DL is a sub area of Machine Learning that has solved increasingly complicated applications with increasing accuracy [19]. Deep Learning architectures such as Convolutional Neural Networks (CNN), Deep Belief Networks and Recurrent Neural Networks (RNN) have been utilized in computer vision, speech recognition, natural language processing, among other areas. They have produced some results comparable or even superior to human experts [46]. CNNs were first proposed by [38]. They are similar to traditional Neural Networks but they use a convolution operation in one of the layers instead of matrix operations. They are especially useful for time series data and grid-like data topologies and have been very successful in practical applications such as image classification and were recently proposed for text classification [26]. Figure 3 shows a diagram of a Convolutional Neural Network using sliding filters to analyze text (System calls) input data, where the convolution is applied in the first layer. A discrete convolution operation in Deep Learning can be defined as:

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a),$$

where $x$ is an input measurement on time index $t$, $a$ is the age of a measurement, $w$ is a weighting function (also known as the kernel) that depends on the age of measurement.

Subsequent layers in CNN are normally composed of classical Deep Neural Network full connected neurons. They are usually made of a higher amount of hidden layers, which require special kinds of methods for updating their neuron values. Sigmoid and rectified linear units (ReLUs) are common activation functions $\phi(x)$ used by CNN.

3.6 Generative Models

Traditional Machine Learning models used for classification employ a discriminative approach, they process input data and give a probabilistic membership value to a certain class. On the other hand, there are ML methods that try to learn the probability distribution function that generates the training data (input data space) [19]. Those methods are called generative and are useful in practical applications to create or simulate new training data. These methods have been recently used for instance to create new images from huge previous image datasets.

Recurrent Neural Networks have been used as generative methods with important success in applications. Long Short Term Memory (LSTM) networks were chosen in this research. LSTM networks have an explicit memory cell and are able to capture long-term dependencies in sequential
Fig. 3 A Convolutional Network for text like data processing

data. Formally they can be defined as the following set of equations:

\[
\begin{align*}
    f_t &= \sigma_f(W_f x_t + U_f h_{t-1} + b_f), \\
    i_t &= \sigma_i(W_i x_t + U_i h_{t-1} + b_i), \\
    o_t &= \sigma_o(W_o x_t + U_o h_{t-1} + b_o), \\
    c_t &= f_t \odot c_{t-1} + i_t \odot \sigma_c(W_c x_t + U_c h_{t-1} + b_c), \\
    h_t &= o_t \odot \sigma_h(c_t),
\end{align*}
\]

(6)

where \(x_t\) is the input vector at a given iteration \(t\), \(h_t\) is an output vector, \(c_t\) is a cell state. \(W\) and \(U\) are parameter matrices and \(b\) a bias vector. \(f_t\), \(i_t\) and \(o_t\) are gate vectors, \(f_t\) is a forget gate vector, \(i_t\) is the input gate vector. Finally, \(o_t\) is the output gate vector. Further, we give more details on how we have adapted the LSTM network to our training data.

4 System design

In this study, we propose the integrated usage of Security by Isolation (SbI) with Linux containers and Deep Learning methods to analyze real time monitoring data of processes running inside virtualized HTC infrastructure, as well as the utilization of generative methods to improve the required training data. We introduce a hybrid supervised classification approach using word2vec for feature selection and pre-processing and Convolutional Neural Networks (CNN) for discrimination between normal and malicious classes. Our study also employs Recurrent Neural Networks (RNN) for data generation on the training steps. Arhuaco was designed as a proof of concept implementation based on this proposed methods, with focus on Grid computing. Therefore it is designed to provide security with a Grid based threat model approach based on the one introduced in [18]. This can be applied to other types of distributed HTC environments. In a computing Grid, an adversary may have several goals:

- Steal sensitive data such as private encryption keys, user’s certificates, tokens or credentials.
- Compromise user’s machines to distribute malware and steal valuable user information.
- Carry out a Denial of Service attacks.
- Abuse the Grid computational resources for criminal or not allowed activities, for instance, to deploy botnets or mining crypto-coins.
- Damage the organization reputation by using resources to attack other organizations.

To achieve these goals, an attacker could use several methods:

- Exploit unknown or not fixed software/hardware vulnerabilities.
- Listen to user network to gather sensitive clear text information.
- Perform a man in the middle attack.
- Tamper with user’s jobs.
- Escalate privileges.
- Access sensitive server configuration data.

In the next subsections, a detailed information about the design and implementation of Arhuaco is given, based on our proposed contributions. We also describe how our system works under the described threat model.

4.1 Linux Containers for Isolation

We require an isolation technology easily adaptable to the Linux powered Grid computing for High Energy Physics (HEP). Linux Containers (LC) were selected to provide SbI given their security vs performance balance [13]. LCs provide in addition a very important feature, network isolation. They make it possible to create an encrypted virtual networks inside a physical or another virtual network, in order to restrict processes running inside to access sensitive assets. This is fundamental in Grid computing, where sites may be
sharing resources with other projects or experimental infrastructure. For instance, there is a Grid site at the ALICE HLT cluster, sharing physical resources with the sensitive LHC experiment network [6]. Therefore virtual network isolation is used to avoid breaches. Another fundamental feature of Linux Containers for our this study is the monitoring power they grant. Since it is possible to encapsulate a set of processes with their own view of the entire system, it is also possible to capture specific per process metrics that allow us to analyze their isolated behavior. We are able to capture resource consumption data such as CPU, memory and disk, network connection data, and system calls for a specific container and as a consequence for each Grid job. Therefore, we can detect with better precision the source of a security incident or even collect forensics data for further analysis. Figure 4 is a schema of the desired isolation characteristics. On the left, Grid jobs run without isolation, being able to affect other jobs or the underlying system. On the right, Grid jobs are isolated by LCs, each one of them run in a reduced version of the whole system, so they have no access to other jobs or sensitive resources in the working nodes.

Traditional Grid systems use batch engines such as Condor [55] for scheduling jobs in distributed environments. To run containers instead of standard batch jobs, we need modern orchestration tools that concede us the ability to execute containers over a shared cluster. There are several popular alternatives including Google Kubernetes [41], Apache Mesos [22], and Docker Swarm [32]. In the system implementation section, we describe the reason for selecting Docker Swarm to be the first container engine that Arhuaco interacts with.

4.2 Deep Learning for Grid job classification

Popular industrial IDS such as Snort and OSSEC [44] and [21] use fixed rules and search for known attack signatures in order to find possible attacks. They have problems when unknown or slightly different intrusion methods are employed, so they need to be constantly updated [27]. Machine Learning has been commonly suggested in Intrusion Detection for the modeling and analysis of log and network data for autonomous classification of security incidents. As depicted in Figure 5, in this research we apply dynamic analysis of Grid jobs monitoring data for real time intrusion detection, which means analysis of operation system (Linux) processes. A supervised classification approach is implemented in Arhuaco. We propose the usage of a Convolutional Neural Network architecture based on the one introduced in [26] for English sentences classification and utilized in [15] for static binary file classification according to their x86 machine code instructions.

4.3 Feature extraction

As mentioned before, this study employs system calls and network connection traces as input data. They are encoded in a human readable format, thus Natural Language Processing (NLP) methods allow us to build a convenient language model. Recently introduced Deep Learning methods for NLP implement learning word vector representations by neural language models [4]. In these vectors, words are projected from a $1 - o - V$ encoding, where $V$ is the number of different words available (vocabulary size), in a lower dimensional vector space using Neural Network hidden layers [26]. Therefore, semantically close words in the training corpus are mathematically close in the lower dimensional vector space. The word2vec algorithm [16] was chosen for Arhuaco to create the input features. It is a predictive model for learning word embeddings. Word2vec vectors create suitable inputs for Convolutional Neural Networks since they allow to treat input data as matrices, similar to the array of pixels in an image. Here we refer to tokens instead of words since our dataset can also contain numbers, paths, IP addresses, among other type of data.

As a preprocessing step for the traces, characters that do not increase the amount of available information are deleted. Each trace line of system calls is composed of the type of operation, the opcode number and all its parameters. For network connection information each line has the DNS request,
where

\[ a_{1:n} = a_1 \oplus a_2 \oplus \ldots \oplus a_n, \]

where \( \oplus \) is the concatenation operator, and \( a_{i+k} \) is the concatenation of tokens \( a_i, a_{i+1}, \ldots, a_{i+j} \). These embedding vectors are the result of applying word2vec method on our text input data.

### 4.4 Convolutional Neural Network

In the context of this research, a convolution operation involves a kernel or filter \( G \in \mathbb{R}^{h,k} \), which is applied to a window of \( h \) tokens to produce a new feature. For example, a feature \( z_i \) is generated from a window of words \( a_{i+h-1} \) by:

\[ z_i = f(G \cdot a_{i+h-1} + b), \]

where \( b \in \mathbb{R} \) is a bias term and \( f \) is a non-linear function. This filter is applied to each possible window of tokens in the sequence \( \{a_1, a_2, \ldots, a_n\} \) to produce a feature vector \( z = [z_1, z_2, \ldots, z_{n-h+1}] \), with \( z \in \mathbb{R}^{n-h+1} \). A max-over-time pooling operation is then applied to the feature vector, taking the maximum value \( z^* = \max z \) as the only feature resulting from this filter. The most important feature, one with the highest value, is kept for each feature map. The same process is repeated with multiple filters of different window sizes, to obtain multiple features. These features are passed to a fully connected \( \text{ReLU} \) layer whose output goes to the last dense layer with \( \text{Sigmoid} \) activation with outputs corresponding to the probability distribution over labels (normal and malicious in our problem setup).

For the contrasted classification method - the Support Vector Machine (SVM) - we used the well established Bag of Words (BoW) model [39] to create its input feature vectors. In the BoW we first create a vocabulary with the list of all possible tokens is the training set. Then we reduce this vocabulary by using only the most used tokens. We created a vector where each component is the number of times a given token appears in the analyzed set. An alternative method is the Continuous Bag of Words (CBOW), which predicts target words from source context words.

### 4.5 Recurrent Neural Network (RNN) for training data generation

A character level language model has been selected as a generative method for Arhuaco. The objective of this model is to predict the next character in a sequence. Given a training corpus \( (c_1, \ldots, c_T) \), where \( c_i \) is a single character and \( T \) is the total number of characters. A Long Short Term Memory (LSTM) RNN is utilized to determine the sequence of its output vectors \( (o_1, \ldots, o_T) \) by a sequence of distributions \( P(c_{i+1} | c \leq i) = \sigma(o_i) \). Here \( \sigma \) is the \text{softmax} distribution defined by:

\[ P(\sigma(o_i) = j) = \frac{\exp(o_{ij})}{\sum_k \exp(o_{ik})} \]

The objective function is to maximize the total log probability of the training sequence \( \sum_{t=0}^{T-1} \log P(x_{t+1} | x \leq t) \). This implies that the LSTM learns a probability distribution over sequences. We can then sample from the conditional distribution \( P(x_{t+1} | x \leq t) \) to get the next character in a generated string and provide it as the next input to the LSTM [52]. After the training process has finished we can generate new data that can be used as extra training data in order to extend the generalization capabilities of a classification system [15].

### 4.6 Arhuaco design architecture

A diagram of Arhuaco architectural components is shown in Figure 6. The execution engine provides an interface with a selected container scheduling engine according to configuration parameters. Then, the executed containers are monitored, extracting real time data for security analysis. The data is processed by the previously described feature extraction mechanism. Furthermore, these preprocessed input feature vectors are sent to the classification and generative modules. They can provide feedback to each other. Any suspicious incident is processed by the response engine. This can be configured with predefined actions, such as sending alerts to administrators, stopping suspicious jobs, or collect information for offline analysis (forensic).

### 5 Implementation

The Arhuaco prototype was developed in Python. It provides interfaces for Grid frameworks, container engines and data collection tools. Among the alternatives for Linux Container engines, to the most popular belong Docker [32], Rocket [33], Singularity [28], and LXC [8]. Arhuaco supports Docker in its first stage, given its broad adoption in industrial applications and its default security measures. To be able to execute grid jobs inside LCs, three solutions were tested: Kubernetes [41], Apache Mesos [23], and Docker Swarm. Docker Swarm was chosen due to its simplicity and fast deployment in testing environments. In addition, it
provides out of the box encrypted virtual networking. Further, we may create interfaces with other container scheduler engines. A testing ALICE Grid site based on AliEn [3], the ALICE Grid middleware, was deployed in a local Linux cluster at the Goethe University in Frankfurt. It has 5 Ubuntu 14.04 nodes. A custom CentOS 6 based Docker image and an AliEn interface for Docker Swarm were developed. CVMFS [2] was installed on the hosts and shared as a volume inside the AliEn containers to grant access to High Energy Physics libraries. One job per container is executed by design, which is useful to increase the traceability between different jobs. Besides, it is the natural micro service model for Linux Containers.

For the training and validation of our proposed classification and generative algorithms, a dataset composed of normal and malicious system call and network connection logs was collected. Instead of creating our own set of malicious binary samples we have used a set of 10,000 Linux malware samples downloaded from a security research web site [63]. This allows us to cover a bigger range of malicious activities that would be very time consuming and error prone to do manually. Regular Grid jobs were also collected from the ALICE Grid production environment, using our test Frankfurt site, to improve the training data. We ran the samples and collected the same set of metrics for both types of binaries. We executed them inside containers and used the isolation and monitoring features to collect every system call and network connection. These are some examples of the collected data:

```
Malware:
* IP.x IP.y irc.qeast.net 1 C_INTERNET ...
* file open fd 4 name /etc/passwd ...

Grid job:
* IP.z IP.w alice-disk-se.gridka.de 1 ...
* file access res 2 ENOENT name /cvmfs/alice.cern.ch/x86 ...
```

We utilized Sysdig [53] for collecting system calls and Bro IDS [36] for network connection data. For executing the malware samples a testing environment without Internet access was deployed, using Inetsim [24] for network connection emulation. We have also employed Cuckoo sandbox [35] to isolate and monitor these runs. Table 1 shows a summary of the collected dataset. In the Arhuaco online setup, once the training is finished, the system call and network traces collection is done in real time, as well as the classification.

Table 2 shows a summary of the obtained samples after the feature selection step. A representation of the implemented test as part of the ALICE Grid can be seen in Figure 7.

```
Table 1 Full preprocessed available datasets

| Dataset          | Normal | Malware |
|------------------|--------|---------|
| System call      | 12GB   | 8.2GB - 127’054.763 lines |
|                  | 127’100.000 lines |  |
| Network          | 868KB  | 108KB - 2.937 |
|                  | 20.733 lines |  |

Table 2 Used training and validation data after feature extraction

| Dataset              | Training | Validation |
|----------------------|----------|------------|
| System calls traces  | 10’000.000 | 100.000    |
| Network traces       | 20.000   | 2.000      |
```

We have implemented the Deep Convolutional Neural Network (CNN), Support Vector Machine (SVM) and Recurrent LSTM Neural Network by using the Python library Keras [11] with Theano [56] as a backend. Keras simplifies the development of Deep Learning algorithms and provides parallel computing capabilities powered by Theano.
### Table 3 Custom CNN parameters

| Parameter          | System calls | Network |
|--------------------|--------------|---------|
| Embedding dimension| 20           | 10      |
| Filter sizes       | 3, 4, 5      | 2, 3    |
| Total number filters| 20          | 3       |
| Optimization function | SGD        |         |
| Learning rate      | 0.001        |         |
| Momentum           | 0.80         |         |
| Decay              | $10e^{-6}$   |         |

### Table 4 Shared SVM and CNN parameters

| Dataset        | m | l | n |
|----------------|---|---|---|
| System call    | 7 | 6 | 42|
| Network        | 5 | 1 | 5 |

It also supports TensorFlow [1]. It is convenient for High-throughput Computing (HTC) applications, since it can share resources with other applications running in parallel, and it is strongly focused on using GPU to increase the parallel processing performance. Another Python library, Gensim [40] was employed for word2vec extraction of embedding vectors. Due to the huge size of the training corpus, it has the functionality to deal with data that does not fit in main memory.

The CNN hyper-parameters have been selected by an empiric grid search. They are listed in Table 3. We use momentum and parameter decay to ensure the model convergence, and dropout to prevent overfitting. For the Support Vector Machine, we chose the Hinge loss function and the Adadelta optimizer. The parameters $m$, $l$, and $n$ described in the previous section are shared among the two models. They are listed in Table 4. These last parameters were selected to keep a good balance between the classification accuracy of normal and malicious classes and the ability to detect intrusions in real time. For the LSTM Network, the chosen optimizer is Root Mean Square Propagation, with a learning rate of 0.01, and a categorical cross entropy as loss function.

### 6 Evaluation

In this section, an empiric evaluation of the performance impact, classification ability and data generation effectiveness for the methods implemented in Arhuaco is described. Here the goal was to answer the following questions:

- Does using LC for isolation and system call monitoring create a big performance impact? If that is the case, is it critical in comparison to the increment in security provided?
- Does the CNN for classification of job traces provide better accuracy and false positives rates than the traditional SVM?
- Does the LSTM Network for data generation improve the training results?

### 6.1 Evaluation methods

We have deployed two type of performance tests. The first with the Linpack benchmark as introduced in [13] to test the throughput. The second measures the performance impact in processing times. For the first test, we ran Linpack jobs while for the second the job is a production ALICE script. We have prepared 3 evaluation scenarios: running jobs on a Linux machine, then in Docker containers and finally in Docker containers with system call interception and processing by Arhuaco. In our performance analysis, the impact of collecting network data from the job is not measured.

Loss, Accuracy (ACC) and False Positive Rate (FPR) are the measurements for the correctness of the compared classification methods. The overall performance of the trained classifiers is evaluated by the Accuracy. This measures the number of instances that were correct, which are both the True Positives and True Negatives, over the entire size of the dataset, which is the number of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). It is calculated as:

$$\text{Accuracy(ACC)} = \frac{(TP + TN)}{(TP + TN + FP + FN)},$$

$$\text{FalsePositiveRate(FPR)} = \frac{FP}{FP + TN},$$

where False Positives (FP) is the number of misclassified instances of a certain category over the number of all instances that are classified as that category. The ACC and FPR values are defined in the range $[0, 1]$, where 1 is the best possible value for ACC and the worst for FPR. On the other hand, 0 is the best value for FPR and the worst for ACC. They can also be interpreted as percentage values in the range $[0\%, 100\%]$.

### 6.2 Performance impact results

The performance evaluations were carried out in our Frankfurt testing Grid site. Each of the 5 machines has identical configuration: 4 Intel Xeon (64 bit) processors for a total 16 cores running at 2.27 GHz and 16 GB RAM. They all have Ubuntu 14.04 as the installed operating system. The container images are derived from CentOS 6, since this is the current recommended distribution to be used with the CERN HEP Grid libraries.
Table 5: Performance impact in throughput measurement

| Setup          | Linpack (GFLOPS) |
|----------------|------------------|
| Native         | 3.7664           |
| Docker         | 3.7506 (-0.4%)   |
| Docker plus sysdig | 3.7463 (-0.5%)   |

Table 5 shows the performance of Linpack jobs on Linux, Docker and Docker plus Arhuaco monitoring. We have executed one job per CPU core, for a total of 16 jobs and have measured the resulting throughput. Figure 8 describes the results of the ALICE Grid job test. Up to 10 jobs instances in parallel were executed. The measurement was the execution time they spend to be completed. Each job does the same tasks, simulation, reconstruction and analysis of the same ALICE HEP data.

6.3 Supervised classification results

Figure 9 and Figure 10 indicate the training and validation accuracy for the proposed Convolutional Neural Network (CNN) and the compared Support Vector Machine (SVM) on the analysis of system call traces, preprocessed by word2vec and BoF. The CNN validation curve is close to the training curve, approaching nearly 99%. Since the SVM model is far smaller, a trend for over-fitting can be seen in the validation curve compared to the training curve. Figure 11 and Figure 12 show a comparison for the ACC and FPR with the validation data. Clearly, the CNN provides a higher accuracy and lower False Positive Rate than the SVM.

Figure 13 and Figure 14 represent the the results for the classification of network traces with our proposed CNN and compared SVM method. As with the system calls case, the CNN shows similar results with the training and validation data, approaching 99%. The SVM shows signs of over-fitting and a lower accuracy. In Figures 15 and 16 we see the comparison of the validation data for accuracy and False Positive Rate. A better accuracy for the CNN is clear in this case as well, however, the SVM exhibits a better FPR.

Table 6 summarizes the results obtained for applying the Convolutional Neural Network and Support Vector Machines on previously unseen testing data. A better accuracy and False Positive Rates for the CNN over the SVM is shown, except in the case of FPR for the network data. This validates the results we have obtained in the training steps and demonstrates the effectiveness of using Convolutional Neural Networks for classification in Arhuaco to detect intrusions, in comparison to utilizing Support Vector Machines, the most popular method used in Grid computing Intrusion Detection Systems.
Fig. 9  Classification accuracy of the CNN applied to system calls

Fig. 10  Classification accuracy of SVM applied to system calls

Fig. 11  Accuracy comparison of CNN vs SVM applied to system calls

Fig. 12  False Positive Rate comparison of CNN vs SVM applied to system calls

Fig. 13  Classification accuracy of CNN applied network data

Fig. 14  Classification accuracy of SVM applied to network data
6.4 Generative model results

As shown in Table 6, the SVM classification results for network connection information produced the worst accuracy in all our tests. Therefore we utilized this same case to prove the effectiveness of the proposed generative technique. The Deep RNN was trained with the available network data corpus and then modified to generate 20% new training data. The new data was concatenated to the original data to create a new training set. Further, the SVM is trained again to measure the new accuracy. The validation data utilized belongs to the original data. Figures 17 and 18 provide a new comparison of the SVM accuracy and FPR after being trained with the additionally generated data. A noticeable improvement can be seen regarding the training with the original data in Figures 15 and 16. This demonstrates the practical benefits of using LSTM for modeling and generating data in the context of Intrusion Detection Systems.

The obtained accuracy for the SVM trained with the newly generated data, applied to unseen network data from the original dataset was 0.8201. There was a 2.38% improvement rate as expected with our approach, in comparison the original value from Table 6, 0.8011. This validates the results obtained in the training steps.

7 Discussion and future work

Regarding the first question we have defined in our evaluation, the performance tests present an execution time overhead of 0.4% when using Linux Containers in comparison with the Linux runs for the Linpack throughput test, and 0.5% when using Arhuaco monitoring. This can be considered as a very small impact. The impact is more considerable when testing the execution time for the ALICE Grid job.

The Docker container generates up to 8.634% of overhead. It is higher, an extra 2.535% when monitoring by Arhuaco is added on top. Although this overhead is not critical, we have implemented some ideas to reduce it. We have a two layers approach, based on user configuration. Arhuaco can detect malicious activities by first intercepting and analyzing network connections and then it can make a deeper analysis by a second layer using the system calls, after suspicious processes detection. Another configurable option is to randomly analyze a small set of jobs running in the Grid, which still can contribute to have an improved level of security. It is important to notice that containers are being increasingly utilized in Grid computing collaborations and as we have shown, adding extra monitoring and analysis by Arhuaco creates an acceptable performance impact. Another point to consider is that there are studies [13] that compare Linux Containers against Virtual Machines (VMs). They demonstrate that VMs create a bigger overhead in the performance than LCs.

The classification algorithm implemented in Arhuaco improves the detection of malicious activities running inside the grid, compared to traditionally employed methods, which responds to the second research question. Convolutional Neural Networks demonstrate a better classification ability than Support Vector Machines for system calls as well as for network connections in Grid jobs. Since our gathered malicious network data is rather small, we have successfully generated new data by a Recurrent Neural Network. We described how it allowed us to improve the classification results for the SVM, giving an answer to the third evaluation question. An interesting point to remark is that our approach of analyzing input as a text data by Natural Language Processing approaches can be easily extended from system calls and network data to inputs from other In-
trusion Detection Systems or different sources of monitoring data. It could also be easily adapted beyond HTC, for instance to monitor Cloud services running in containers over orchestration engines such as Kubernetes and Mesos.

We still have some limitations and topics for further analysis. We will investigate optimizations that we can introduce in Arhuaco for reducing the overhead. This seems feasible given the results for Linpack. Our framework has not been tested in a production environment yet. The obtained False Positive Rate, although small, is still significant if we consider the huge amount of jobs running in the Worldwide LHC Computing Grid, close to 300,000 at any given instant. We should improve the results in this area and also research into methods to inform about the possible security incidents detected. We will explore techniques to protect the privacy of our datasets in order to avoid leaks of sensitive information. We will also investigate in how to employ the distributed nature of the Grid to improve the distributed detection of intrusions. This can be useful for instance, to autonomously inform other Grid sites IDS about security incidents that could spread in the Grid. We are working on further enhancing the isolation provided in our containers by using kernel hardening such as grsecurity. Besides we are currently testing the integration with other container solutions and HTC engines.

8 Conclusions

We have presented Arhuaco, a security monitoring tool for High-Throughput Computing. It employs Security by Isolation for executing and monitoring Grid jobs inside Linux Containers based on multiple sources of monitoring data such as network connections and system calls. It applies Convolutional Neural Networks to classify Grid jobs data as normal or malicious. It also utilizes a Recurrent Neural Network to learn a data model in order to generate new training samples. The proposed algorithms implemented in Arhuaco improve the security incident detection in Grid computing systems, since it is able to identify the source of an intrusion with higher accuracy. Arhuaco can analyze the huge flow of real time data that monitoring Grid jobs generate. This makes Arhuaco suitable for environments such as the WLCG, the global Grid that analyzes data from the Large Hadron Collider (LHC) at CERN, where millions of jobs are executed every day. By a set of tests carried out in the ALICE Grid as part of the WLCG, we have shown how the proposed algorithms outperform other methods used in Intrusion Detection Systems for Grid Computing.

Datasets and software

Arhuaco is under development. We are discussing the possibility to release it and the training dataset as Open Source software and data.

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