Scalable Microservice Forensics and Stability Assessment Using Variational Autoencoders

Prakhar Sharma, Phillip Porras, Steven Cheung, James Carpenter, Vinod Yegneswaran

Computer Science Laboratory, SRI International

Abstract—We present a deep-learning-based approach to containerized application runtime stability analysis, and an intelligent publishing algorithm that can dynamically adjust the depth of process-level forensics published to a backend incident analysis repository. The approach applies variational autoencoders (VAEs) to learn the stable runtime patterns of container images, and then instantiates these container-specific VAEs to implement stability detection and adaptive forensics publishing. In performance comparisons using a 50-instance container workload, a VAE-optimized service versus a conventional eBPF-based forensic publisher demonstrates 2 orders of magnitude (OM) CPU performance improvement, a 3 OM reduction in network transport volume, and a 4 OM reduction in Elasticsearch storage costs. We evaluate the VAE-based stability detection technique against two attacks, CPUMiner and HTTP-flood attack, finding that it is effective in isolating both anomalies. We believe this technique provides a novel approach to integrating fine-grained process monitoring and digital-forensics services into large container ecosystems that today simply cannot be monitored by conventional techniques.

I. INTRODUCTION

Application containerization is becoming the dominant technology to architect and deploy microservice applications and software services. IDC Research predicts that by 2023 more than 500 million applications and services will be developed using cloud-native containerization services [4], which is roughly the same number of applications that have been developed over the last 40 years combined. Containerization has become integral to the security and management of front-line software services and sensitive data processing applications across all major industries in our economy.

However, container-based microservice ecosystems pose a myriad of challenges to the integration of security services, runtime management, and forensics collection for security incident response; most significant of which is scaling these services to manage modern container pipelines. Process monitoring and forensic logging impose significant costs to container workload overhead, as they consume CPU cycles, network bandwidth, and data storage, to deliver and store information to log repositories. In fact, industrial scale container ecosystems (thousands of application instances and beyond) are largely out of reach of conventional process-level monitoring and forensic services. Nevertheless, fine-grained process monitoring remains an important service, and indeed a compliance requirement, for enabling security, fault management, and damage assessment.

This paper examines two critical questions pertaining to the secure runtime management of such large-scale container ecosystems. First, how can we conduct massively scalable monitoring of containerized applications to identify when containers become unstable or subverted? Second, when runtime instabilities are perceived, how can we capture enough fine-grained digital forensics to drive an incident response or fault analysis?

For container DEVOPS environments, process visibility is commonly achieved through some form of extended Berkeley Packet Filter (eBPF)-based tracing, such as through services like Sysdig [7] and Chisel [19]. These tools offer a significant performance advantage over typical host auditing services for process system-call logging. eBPF extends a host kernel with logic to trap key system calls on entry or exit from the kernel, providing a fine-grained view of process-internal runtime behavior to drive intrusion detection, fault analysis, and other forms of anomaly detection.

We propose a new strategy for conducting a computationally-efficient local analysis of container runtime behavior. This is done through an extraction of activity vectors that captures statistics and attributes from a container’s eBPF-based forensics produced during intervals of runtime operation. An activity vector is input to a VAE that determines the extent to which the vector fits the container’s trained stable baseline runtime model. VAEs are robust and efficient in performing event-based pattern analysis [21], [22]. We introduce a VAE-driven adaptive forensic publisher, which produces a runtime stability assessment to determine the depth of forensic services published to the remote log repository. During an interval of runtime stability, the VAE-based forensic publisher delivers an activity model that captures the modality of the application as it was observed through its eBPF-derived system-call forensics. An activity model is a highly reduced representation of the forensic data, requiring a fraction of transport and storage cost. During intervals not matching the trained runtime pattern, the publisher delivers the interval’s forensic log along with the activity model. Analytics are then performed on the forensic logs to isolate evidence of errors or faults, as well system-call actions that may indicate malicious operations performed during the unstable runtime interval.

We present an overview of the VAE algorithm for interval-based container stability assessment and our adaptive forensic publisher service. The system has been implemented and tested within Docker and Kubernetes environments. Results of a comparative performance assessment of the VAE-based forensic publisher versus conventional process-level forensic collection services are presented. These results demonstrate the potential for deep-learning optimized forensic publishing ser-
services to enable fine-grained process monitoring and forensic-based incident response service to scale within ecosystems that today are beyond the resource consumption limitations of conventional monitoring techniques.

II. VAE DESIGN

Given any dataset \( X \) drawn i.i.d from true data distribution \( p_{data} \), variational auto-encoders [8] (VAEs) aim to learn an encoder decoder pair that enable drawing new samples \( x_{new} \) such that \( x_{new} \sim p_{data} \) (\( \sim \) signifies a sample drawn from a probability distribution). The encoder and decoders are usually represented by neural networks. The generative process of VAEs involves learning a low dimensional latent space and is defined as:

\[
    z_{new} \sim p(Z) \quad x_{new} \sim p_{\theta}(X|Z = z_{new})
\]

where \( p(Z) \) is a fixed prior distribution over latent space \( Z \). VAE operation can be broken down into two parts, first the input is mapped to the latent space via an encoder \( E \) (parametrized by \( \phi \))

\[
    E_{\phi}(x) = z \sim q_{\phi}(z|x) = q(Z|f_{\phi}(x))
\]

and then the latent space is mapped to the original distribution via a decoder \( D \) (parametrized by \( \theta \))

\[
    D_{\theta}(z) = x_{new} \sim p_{\theta}(x|z) = p(X|g_{\theta}(z))
\]

Here \( f_{\phi}(x) \) and \( g_{\theta}(z) \) represent neural networks. The VAE architecture is trained via gradient descent by minimizing the evidence lower bound (ELBO) for each sample \( x \).

\[
    \log p_{\theta}(x) \geq ELBO(\phi, \theta, x) = E_{z \sim q_{\phi}(z|x)} \log p_{\theta}(x|z) - KL(q_{\phi}(z|x)||p(z))
\]

Abstractly, the elements that compose a typical VAE are illustrated at the top of Figure 1. The term \( E_{z \sim q_{\phi}(z|x)} \log p_{\theta}(x|z) \) is called the reconstruction error or reconstruction loss (\( L_{rec} \)) of each sample, often calculated in practice using the mean squared error (MSE) between the data sample and its reconstruction. For a VAE trained on \( X \sim p_{data} \), \( L_{rec} \) would be high if the sample is not drawn from \( p_{data} \) and would be low for a sample drawn from \( p_{data} \). Post training, \( L_{rec} \) for any new data sample can be used as an indicator of how well the new sample conforms to the original data distribution from which the VAE was trained. Thus, VAEs have been used for anomaly detection tasks in recent years [2], [3], [21].

Figure 1 also illustrates the major processing layers in our implementation of an eBPF-based container forensic publishing service that employs VAE-based stability assessment.

Forensics Generation: The primary source of process forensics are captured via eBPF and Sysdig, configured to generate forensic records for a selected set of system calls. Our configuration tracks a default set of 72 Linux system calls, which represent the most commonly audited system calls [10] [13] to drive security incident analysis, Host IDS analytics, and application fault analysis. These systems calls can be categorized into 10 classes of activity: process events, the set-user-id family of events, network events, file and directory access events, kernel module load events, process and application virtualization event, file descriptor replication, file attribute events, filesystem mount events, and IOCTL events. In addition, the forensic stream can be augmented with sensor event streams, application log events, system events, and system resource metrics.

Activity Vector Summarization: At regular temporal intervals, a forensic summarization service, or summarizer, computes a vector of statistics from an analysis of the forensic stream produced during the interval. These statistics include continuous and categorical measures of events (or even N-grams), invocation counts, response codes, and other arguments extracted from the forensic data produced during the interval. The temporal window is configurable, with a default value of 30 seconds. The activity vector provides a concise salient behavioral summarization of the runtime pattern observed, and used by the VAE to assess each runtime interval against its trained data model (derived from a set of activity vectors produced during the application’s training period).

Adaptive Forensic Publisher: We introduce an adaptive forensic publisher that alters the depth of forensics published based on the VAE’s analysis of the container activity vector. Here, the depth of forensics published to a remote forensic repository is selected based on whether the container’s latest runtime interval is found to be consistent with the vetted-stable forensic corpus from which the VAE was trained. During intervals in which the VAE-processed forensic stream produced a low reconstruction error, the VAE latent model M is published to Elasticsearch. Otherwise, both M and the cached forensic stream for this interval are published to Elasticsearch. The cache, depending on the local host configuration, can host...
forensics across multiple prior intervals, enabling the publisher to serve Elasticsearch with prior intervals upon request.

**VAE Stability Evaluation:** With each incoming summarizer message \( x_{in} \) per container, the publisher checks whether trained normalization and VAE models for that container exist. They are used to calculate \( L_{rec} = MSE(x_{in}, D_{\theta}(E_{\phi}(x_{in}))) \), which is then compared to a pre-set reconstruction error threshold \( r_{th} \). \( L_{rec} > r_{th} \) is considered to be a drift in stability, otherwise the operating mode is considered stable.

**VAE Training:** In case a valid container VAE model does not exist, each incoming vectorized summarizer message is stored until a pre-decided number of total summarizer messages have been accumulated into a dataset. The dataset features are normalized and the VAE is trained on the normalized dataset using mini-batch gradient descent. Post accumulation, both the normalization model and the VAE neural network model are stored to be used for evaluation. Important parameters that govern training and evaluation are explained in the Appendix.

### III. Evaluation

#### A. Evaluating Multi-container Workload Overhead

We conducted a series of comparative assessments of VAE-based publishing overhead to that of a standard eBPF-based container monitoring system. The standard system performs interval caching, and utilizes the Elasticsearch bulk-API transfer protocol per interval, offering a reasonable and performance-aware implementation for typical process forensic publishing. We consider CPU overhead, processing time, network transport overhead, and Elasticsearch data-storage costs for comparison.

We used the Falco system-call test-generation container provided by the Falco project [18]. The experiment employed the use of eBPF and Sysdig, configured to capture 72 Linux system-calls that are commonly used for forensic security analysis and error diagnosis. The experiment was hosted on an Intel(R) Xeon(TM) CPU 3.20GHz, 8 core, 16GB DDR2 DRAM, 2TB SATA II Drive, and Docker hosted on Ubuntu 16. We conducted the performance tests using 10, 20, 30, 40, and 50 container instances on our host, with 30-second caching intervals, and then averaged to performance statistics over 50 intervals.

| Focal container instances | Per 30-sec interval system call count | Per 30-sec interval CPU cycles | Per 30-sec interval processing time |
|----------------------------|--------------------------------------|-----------------------------|----------------------------------|
|                            | Standard                             | VAE                         | Standard                         | VAE                         |
| 10                         | 18K avg. syscalls                    | 421 B                       | 4.0 B                            | 4 secs                       | 90 ms                       |
| 20                         | 36K avg. syscalls                    | 809 B                       | 8.0 B                            | 6 secs                       | 170 ms                      |
| 30                         | 55K avg. syscalls                    | 1.3 T                       | 12.6 B                           | 13 secs                      | 260 ms                      |
| 40                         | 70K avg. syscalls                    | 1.6 T                       | 17.7 B                           | 18 secs                      | 430 ms                      |
| 50                         | 90K avg. syscalls                    | 2.7 T                       | 22.7 B                           | 28 secs                      | 510 ms                      |

**Table 1.** Per interval CPU cycles and processing time for all forensic production and publication computation activity

Table 1 shows the per-interval CPU costs and processing time incurred by the standard publishing method versus the VAE, for each of five test processing loads. `Perf(1)` (Linux command) was used to compute CPU cycles per the two forensic process algorithms, excluding consideration of the eBPF and systemd costs, as these two modules are used and configured identically for both publishing systems. Of particular interest is the observation that at 50 container instances (90K average syscalls per interval), the standard publishing method requires approximately 28 seconds to publish the forensics during the average 30 second interval. In general, when a publisher’s processing time exceeds the collection interval, this is considered to point of saturation, as it takes longer to publish the records than to produce them. In contrast, under the same 50 container workload, the VAE requires only 510 milliseconds to conduct its stability analysis and publish results.

Table 2 shows the network transport overhead and storage costs for the standard publisher versus the VAE. These costs reflect to overhead involved in transferring forensic and container-stability assessments to a forensics data center for incident and fault analysis. The network transport cost is captured in bytes observed from `tcpdump` captured from the publisher’s communications with Elasticsearch over each 5-minute experiment. The table also shows the average byte storage increase incurred by Elasticsearch during each 5-minute experiment.

**Table 2.** Network transport and Elasticsearch data-storage costs for forensic production and publication

**B. CPUMiner: Detecting Container Hijacking using Microservice Stability Assessment**

In addition to performance analyses, we conducted stability-veracity assessments to assess whether activity vectors captured during stable operations correspond to a low reconstruction error from a trained model. Periods in which nonmalicious and non-error related operations produce reconstruction errors above threshold represent incompleteness in the training set and, depending on their frequency, may indicate a need for enhanced model retraining. Another assessment perspective is the need to validate that encounters with operations not represented in the trained model will be recognized as unstable intervals by the VAE. Our assessment is applicable to a range of test scenarios, including application hijacking, hardware failures, infrastructure faults that impact the container, network attacks, and other fault and attack related scenarios.

Table 3 illustrates an assessment test in which an Nginx-trained VAE observes a series of runtime intervals during
which a malicious CPUMiner application is integrated into the Nginx container. The assessment begins with intervals of normal Nginx operation (a shell script that fetches the index page once per second). As the assessment proceeds, the container experiences a login shell, followed by the issuing of various shell commands. As these actions unfold, the VAE’s reconstruction error grows dramatically, by orders of magnitude as shown in the table. Next, the VAE observes the downloading and compilation of CPUMiner, a common application that is installed into hijacked containers to mine Bitcoins. The VAE produces an astronomical reconstruction error from the initial baseline Nginx operations. Finally, CPUMiner is initiated in the container, continuing the high reconstruction pattern indefinitely, or until CPUMiner no longer pollutes the container’s interval activity vectors.

### Activity | VAE reconstruction error
--- | ---
Normal Nginx processing | 0.014993
Connect with bash shell | 6.298320
Execute shell commands | 1.352e+13
CPUMiner package download | 19390605381.8
CPUMiner execution | 344375512

Table 3. Interval reconstruction errors from a container operating an Nginx-trained VAE to a gradual progression of actions that are used to download CPUMiner and install it within the container.

**C. HTTP Flooding Attack: Detecting Flood Attacks using Microservice Stability Assessment**

![Graph](image)

3. Reconstruction errors during a cyclical HTTP-flood attack on the AtSea_app container

We extend the stability-veracity assessment to a Docker-based demo application experiencing an HTTP flood attack. We used [AtSea](1), a containerized Java REST application with a database for product inventory, customer data, and orders, a shopping cart, a Nginx reverse proxy implementing HTTPS and a payment gateway to simulate certificate management. We used Golang-httpflood to simulate large number of HTTP requests to overload the AtSea containers. An instance of the VAE is trained for the atsea_app container and the Golang-httpflood is invoked cyclically for 1 minute intervals with and 4 minutes of inactivity. Figure 3 shows trained VAE reconstruction errors for such an attack. The spikes correspond to attack durations.

### IV. Related Work

The topic of anomaly detection in microservices has received recent research attention. Ohlsson uses Robust Principal Component Analysis (RPCA) techniques to detect microservice anomalies. Akrami et al. describe the use of Markov Models to detect anomalous container behavior. Magableh uses deep Q-learning networks (DQNs) to build self-adaptive agents for performance optimization. Other recent works investigate the applicability of deep learning techniques, specifically VAEs to the networking domain. Gan et al. and Pol et al. apply a version of VAEs called conditional VAEs for root cause analysis in cloud microservices.

### V. Conclusion and Future Work

We present a method to transform container process-level forensics into interval-based abstract activity vectors, and then input these vectors to a VAE that produces a metric of container runtime stability. This metric is then used to drive an adaptive forensic publisher that alters the depth of information it stores. The approach enables performant determination of the runtime stability of large numbers of containers and isolation of forensic data for deeper analysis. A comparative analysis of a VAE-optimized publisher versus standard process-level forensic auditing shows that our approach reduces CPU, network, and data storage overhead by orders of magnitude. The results suggest that fine-grained process-level monitoring can be successfully scaled to large container ecosystems that are today outside the resource-consumption costs of traditional forensic data collection services. Future work includes setting the process-event capturing time window dynamically to make it difficult for an adversary to spread the attack over multiple windows; and extending the list of process level events currently being captured for summarization (details provided in the Appendix).
Appendix

VAE Configuration: The encoder and decoder modules of the VAE are instantiated each with three hidden layers, each layer has 16 filters in a fully connected fashion. The dimension of the latent model is chosen to be 10. The network is trained with the Adam optimizer with learning rate $10^{-4}$, $\beta_1 = 0.9$, and $\beta_2 = 0.999$. The network is trained for 100 epochs. These hyperparameters were chosen after a grid search on the parameter space for the specific summarizer dataset per-container. The summarizer dataset for each container is normalized using a min-max scaler that is also stored with the VAE model for the purpose of data normalization at test time.

Evaluation Scheme: We used the perf tool for CPU profiling. Perf stats are captured by attaching the tool to the process IDs of Sysdig chisel, summarizer, and publisher processes running on the Linux test machine. Networking specifics are extracted using a running tcpdump process. Storage usage metrics are extracted from elastic search running on a separate server.

Reconstruction error and reconstruction threshold: We employ VAE reconstruction error for each new sample as an indicator of stability. Throughout training, the VAEs minimize the reconstruction error on a dataset as a means of learning the data distribution. A sample training curve for a VAE trained on a dataset is represented in Fig. 4. The training reconstruction error settles to $r_{last}$ after epoch 40.

![VAE reconstruction error](image)

Fig 4. Reconstruction errors during training. VAE train reconstruction error settles to $r_{last}$ after epoch 40.

For each new sample, deviation from $r_{last}$ signifies that the data sample is different from the original training data or is out of distribution. Owing to this fact, we set the reconstruction threshold $r_{th}$ in two major ways for our experiments:

- **Based on a heuristic/experience:** This approach sets $r_{th}$ based on observed reconstruction errors generated during an unstable period.

- **$k$ standard deviations away from the mean:** This approach records the mean ($r_{mean}$) and standard deviation ($r_{sd}$) of training reconstruction errors in the last training iteration. The reconstruction threshold is then set using the following formula: $r_{th} = r_{mean} + k * r_{sd}$ where $k$ is set by the user. This approach has the benefit of making the VAE more flexible or conservative based on the value of $k$.

Summary of Forensic Events: We used a (non-exhaustive) list of the following kernel events:

- **Process Events:**
  - common fork __x64_sys_fork/ptregs
  - common vfork __x64_sys_vfork/ptregs
  - 64 execve __x64_sys_execve/ptregs
  - 64 execveat __x64_sys_execveat/ptregs
  - common exit __x64_sys_exit
  - common kill __x64_sys_kill
  - 64 ptrace __x64_sys_ptrace
  - common ptrace __x64_sys_ptrace
  - common arch __x64_sys_arch_ptrace
  - x32 execve __x32_compat_sys_execve/ptregs
  - x32 ptrace __x32_compat_sys_execveat/ptregs

- **Set User ID Family Events:**
  - common setuid __x64_sys_setuid
  - common setgid __x64_sys_setgid
  - common setpgid __x64_sys_setpgid
  - common setsid __x64_sys_setsid
  - common setreuid __x64_sys_setreuid
  - common setregid __x64_sys_setregid
  - common setgroups __x64_sys_setgroups
  - common setegid __x64_sys_setegid
  - common setegid __x64_sys_setreuid
  - common seteuid __x64_sys_seteuid
  - common setfsgid __x64_sys_setfsgid

- **Network Events:**
  - common socket __x64_sys_socket
  - common connect __x64_sys_connect
  - common accept __x64_sys_accept
  - common bind __x64_sys_bind
  - common listen __x64_sys_listen
  - common accept4 __x64_sys_accept4

- **File and Directory Access Events:**
  - common open __x64_sys_open
  - common close __x64_sys_close
  - common openat __x64_sys_openat
  - common mkdir __x64_sys_mkdir
  - common rmdir __x64_sys_rmdir
  - common rename __x64_sys_rename
  - common creat __x64_sys_creat
  - common link __x64_sys_link
  - common unlink __x64_sys_unlink
  - common symlink __x64_sys_symlink

- **File and Directory Access Events (cont.)**
  - common mknod __x64_sys_mknod
  - common mkdirat __x64_sys_mkdirat
  - common mknodat __x64_sys_mknodat
  - common unlinkat __x64_sys_unlinkat
common renameat __x64_sys_renameat
– common linkat __x64_sys_linkat
– common symlinkat __x64_sys_symlinkat
– common fchmodat __x64_sys_fchmodat
– common renameat2 __x64_sys_renameat2
• Kernel Module Load Events:
  – 64 create_module
  – common init_module __x64_sys_init_module
  – common delete_module __x64_sys_delete_module
  – x32 kexec_load __x32_compat_sys_kexec_load
• Process/App Virtualization Event:
  – common clone __x64_sys_clone/ptregs
  – common clone3 __x64_sys_clone3/ptregs
  – process_vm_readv
  * 64 __x64_sys_process_vm_readv
  * x32 __x32_compat_sys_process_vm_readv
  – process_vm_writev
  * 64 __x64_sys_process_vm_writev
  * x32 __x32_compat_sys_process_vm_writev
• File Descriptor Replication:
  – common dup __x64_sys_dup
  – common dup2 __x64_sys_dup2
  – common dup3 __x64_sys_dup3
• File Attribute Events:
  – common chmod __x64_sys_chmod
  – common fchmod __x64_sys_fchmod
  – common chown __x64_sys_chown
  – common fchown __x64_sys_fchown
  – common lchown __x64_sys_lchown
  – common fchownat __x64_sys_fchownat
• Filesystem Mount Events:
  – common mount __x64_sys_mount
  – common umount2 __x64_sys_umount
  – common fsmount __x64_sys_fsmount
• IOCTL Events:
  – 64 ioctl __x64_sys_ioctl
  – x32 ioctl __x32_compat_sys_ioctl

These event indicators are extracted from the eBPF forensic log and passed through our summarizer module to be distilled in a numerical vector format. A collection of these vectors form our dataset.

REFERENCES

[1] A. Akkus, “The atsea sample shop,” https://github.com/dockersamples/atsea-sample-shop-app
[2] H. Akrami, A. Joshi, and S. Aydore, “Robust variational autoencoder for tabular data with beta divergence,” ICML Workshop, 2020.
[3] J. An and S. Cho, “Variational autoencoder based anomaly detection using reconstruction probability,” Thesis, 2014.
[4] F. G. et al., “IDC Futurescape: Worldwide IT industry 2020 predictions,” IDC Research, vol. US45599219, October 2019, https://www.idc.com/getdoc.jsp?containerId=US45599219
[5] G. Fernandez and S. Xu, “A case study on using deep learning for network intrusion detection,” arxiv, 2019.
[6] Y. Gan, D. Lo, S. Dev, and C. Delimitrou, “Sage: Leveraging ml to diagnose unpredictable performance in cloud microservices,” Machine Learning for computer architecture and systems, 2020.
[7] S. Incorporated, “Welcome to Sysdig!” https://github.com/draios/sysdig
[8] D. Kingma and M. Welling, “Auto encoding variational bayes,” International Conference on Learning Representations, 2014.
[9] Leeon123, “The golang httpflood,” https://github.com/Leon123/golang-httpflood
[10] U. Lindqvist and P. A. Porras, “expert-bsm: A host-based intrusion detection solution for sun solaris,” in 17th Annual Computer Security Applications Conference (ACSAC), 2001, New Orleans, Louisiana, USA. IEEE Computer Society, 2001.
[11] B. Magableh, “Deep q learning for self-adaptive distributed microservices architecture,” IEEE Access, 2019.
[12] L. Meng, F. Ji, Y. Sun, and T. Wang, “Detecting anomalies in microservices with execution trace comparison,” Future Generation Computer Systems, vol. 116, pp. 291–301, 2021.
[13] A. Mounji and B. L. Charlier, “Tools for intrusion detection: Results and lessons learned from the asax,” in The First Recent Advances in Intrusion Detection, International Workshop, RAID 1998, Louvain-la-Neuve, Belgium), year = 1998.
[14] P. P. Naikade, “Automated anomaly detection and localization system for a microservices-based cloud system,” Electronic Thesis and Dissertation Repository, 2020.
[15] J. OHLSSON, “Anomaly detection in microservice infrastructures,” M.S. Thesis, 2018.
[16] A. Pol, V. Berger, G. Cerminara, C. Germain, and M. Pierini, “Anomaly detection with conditional variational autoencoders,” ICMLA, 2019.
[17] Pooler, “CPUMiner: a cpu miner for litecoin, bitcoin, and other cryptocurrencies,” https://sourceforge.net/projects/cpuminer/
[18] T. F. Project, “Falco: Cloud native runtime security,” https://falco.org/
[19] L. Pustina, “Sysdig Chisel,” https://github.com/lukaspustina/sysdig_chisel
[20] A. Samir and C. Pahl, “Dla: Detecting and localizing anomalies in containerized microservice architectures using markov models,” in 2019 7th International Conference on Future Internet of Things and Cloud (FiCloud), 2019, pp. 205–213.
[21] H. Xu, W. Chen, N. Zhao, Z. Li, J. Bu, Z. Li, Y. Liu, Y. Zhao, D. Pei, Y. Fend, J. Chen, and H. Wang, Z. mard Qiao, “Unsupervised anomaly detection via variational auto-encoder for seasonal kpis in web applications,” World Wide Web Conference, 2018.
[22] S. Zavrak and M. Iskifiyeli, “Anomaly-based intrusion detection from network flow features using variational autoencoder,” IEEE Access, 2020.