Visualizing Syscalls using Self-organizing Maps for System Intrusion Detection

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Abstract: Monitoring syscall logs provides a detailed view on almost all processes running on a system. Existing approaches therefore analyze sequences of executed syscall types for system behavior modeling and anomaly detection in cyber security. However, failures and attacks that do not manifest themselves as type sequences violations remain undetected. In this paper we therefore propose to incorporate syscall parameter values with the objective of enriching analysis and detection with execution context information. Our approach thereby first selects and encodes syscall log parameters and then visualizes the resulting high-dimensional data using self-organizing maps to enable complex analysis. We thereby display syscall occurrence frequencies and transitions of consecutively executed syscalls. We employ a sliding window approach to detect changes of the system behavior as anomalies in the SOM mappings. In addition, we use SOMs to cluster aggregated syscall data for classification of normal and anomalous system behavior states. Finally, we validate our approach on a real syscall data set collected from an Apache web server. Our experiments show that all injected attacks are represented as changes in the SOMs, thus enabling visual or semi-automatic anomaly detection.

1 INTRODUCTION

Modern computer systems are almost always at risk of being compromised by adversaries. In particular, systems that are connected to a network are subject to malware infections or intrusions executed with the use of sophisticated tools. As a countermeasure, cyber security employs monitoring techniques that continuously check applications and processes for signatures that indicate malicious activities.

However, signature based detection approaches that rely on predefined patterns are unable to detect attacks that have never been observed before. As a solution, anomaly detection enables the disclosure of previously unknown attacks and failures by recognizing repeating patterns as normal system behavior and reporting any deviations from the learned models as potential threats (Chandola et al., 2009).

Adequate and correctly configured data sources are essential for monitoring system behavior in sufficient detail so that manifestations of normal actions as well as attacks are visible. Other than most approaches that analyze network traffic for anomaly detection, the focus of our work lies on system log data, because these logs are semantically more expressive and contain verbose information about almost all events that take place on a system, not only what is communicated with other machines (Creech and Hu, 2014; Liu et al., 2011).

Log messages are frequently collected, processed and analyzed in Security Information and Event Management (SIEM) systems (Kavanagh et al., 2018). These systems usually provide interactive dashboards that visualize monitored log events in real-time. Unfortunately, these visualizations are usually limited to simple charts that display the frequencies of log events relative to each other, or graphs containing time-series of event occurrences. We argue that such simple visualizations do not adequately exploit the potential of representing information contained within log events such as syscalls.

Syscalls (system calls) are a type of log data available in almost all operating systems. Because of their verbosity and fine-grained view on the executed commands, syscalls are frequently used for forensic system analysis after attacks. Shifting to a more proactive analysis, continuously monitoring syscalls using enables automatic anomaly detection and shortens the

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reaction time after incidents, while at the same time reducing the required domain knowledge and time spent with manual analysis.

Existing works that pursue anomaly detection on syscalls often focus on the sequences of syscall types alone, i.e., they only consider a single value from the syscall log lines. However, sophisticated attacks are designed to resemble legitimate syscall execution sequences and thus evade such detection mechanisms (Shu et al., 2015). There is thus a need for anomaly detection techniques that are able to incorporate the execution context in the analysis process. We propose to use argument and return values as well as user and process information to enrich behavior models derived from syscall sequences. It is non-trivial to prepare this high-dimensional data in a way that supports visual review for manual and semi-automatic analysis of syscall sequences and occurrence frequencies. We solve this issue by employing self-organizing maps (SOM) to group and position the syscall log data in a two-dimensional space for visualization.

We summarize our contributions as follows:

- An approach for visualizing system behavior through syscall logs using self-organizing maps,
- enabled by a method for selecting and encoding relevant features,
- with the purpose of manual or semi-automatic anomaly detection.

The paper is structured as follows. Section 2 reviews existing approaches for syscall anomaly detection and visualization. Section 3 provides general information on syscalls and discusses log data preprocessing. Basics on SOM visualizations and advanced visualizations of system behavior are outlined in Sect. 4 and Sect. 5 respectively. Our experiments and the resulting plots are presented in Sect. 6 and discussed in Sect. 7. Finally, Sect. 8 concludes the paper.

2 RELATED WORK

Monitoring syscalls for cyber security has been an ongoing research for many years. One of the earliest popular approaches was proposed by Forrest et al. (Forrest et al., 1996), who used a sliding window to learn a model of normal system behavior from syscall traces that comprises all observed sequences. After the learning phase, any appearing sequence not represented by that model is considered an anomaly.

One critical issue with this and similar succeeding approaches is that they only consider the type of syscall, but omit all other parameters. This results in simpler models, but also impairs the capability of detecting attacks, in particular when attackers design their attacks to resemble benign syscall sequences. In order to alleviate this issue and improve the ability to detect such stealthy or mimicry attacks (Shu et al., 2015), modern approaches attempt to include the context of syscall execution in their analyses.

To address this issue, Abed et al. (Abed et al., 2015) include execution context about closely occurring syscalls by computing their frequencies in sliding time windows. Similarly, Yoon et al. (Yoon et al., 2017) use frequency distributions to cluster syscalls into profiles. In addition to clustering, Shu et al. (Shu et al., 2015) use syscall occurrence frequencies within clusters as well as their co-occurrences relevant for the detection of anomalies.

In many works, neural networks are employed, because of their prominent ability to detect reoccurring patterns in sequences. For example, Kim et al. (Kim et al., 2016) make use of ensembles of a particular type of recurrent neural network named Long Short-Term Memory (LSTM) network, which is able to compute the probability distributions of syscalls that follow a given sequence. Creech and Hu (Creech and Hu, 2014) first identify common sequences of syscalls as words and then use these words as an input to a fast-learning neural network type called Extreme Learning Machine in order to detect phrases, i.e., common sequences of these words.

Our approach employs self-organizing maps, which also belong to the family of neural networks, but their application differs greatly compared to existing work. Rather than explicitly learning the sequences of appearing syscalls, we use SOMs to group and place them in an euclidean space, so that the transitions between them become visually apparent. In addition, our approach incorporates syscall parameters to enable context-aware analysis. Also Liu et al. (Liu et al., 2011) take syscall arguments into consideration, but use them to form semantic units, i.e., groups that describe specific aspects of program behavior.

Providing visualizations that make syscall sequences intuitively understandable is non-trivial. Saxe et al. (Saxe et al., 2012) group and visualize syscall sequences of malware. Their approach relies on a similarity matrix of syscall sequences that is used to arrange malware on a grid so that clusters of related malware emerge. In addition, they provide a method for visual comparison of malware by rendering their subsequences as sequential colored blocks.

Other approaches that support syscall visualizations are usually limited to control-flow graphs generated by linking the learned benign sequences (Eskin et al., 2001). However, these graphs do not take context information into account, and would require

```
type=SYSCALL msg=audit(1551210435.995:23194): arch=c000003e syscall=1 success=yes exit=19 a0=d
a1=42 a2=180 a3=0 items=0 ppid=2249 pid=2253 auid=0 uid=33 gid=33 euid=33 suid=33 fsuid=33 egid=33
sgid=33 fsgid=33 tty=(none) ses=2 comm=”apache2” exe=”/usr/sbin/apache2” key=(null)
```

Figure 1: Sample syscall log line of an Apache process.

Table 1: One-hot encoded sample syscall log line.

syscall_1	syscall_2	syscall_257	success_yes	success_no	exit_-2	exit_0	exit_19	exit_*	...
1	0	0	1	0	0	0	1	0	...

copies of nodes when syscalls appear with different parameters, leading to a high complexity. SOMs alleviate this problem by automatically placing the syscall instances according to the similarity of their parameters, thereby effectively clustering the data.

Girardin and Brodbeck (Girardin and Brodbeck, 1998) experiment with approaches to visualize network data, including SOMs. However, their approach focuses only on labeling the SOM for static analysis or real-time monitoring. While we also discuss labeling for overview, our approach visualizes node hit frequencies and node transitions in the SOM and additionally makes use of sliding time windows to detect changes of consecutively generated SOMs.

3 SYSCALLS

Syscall log data contains a mixture of categorical (e.g., syscall types) and textual (e.g., path names) values and is thus not directly applicable for training a model using machine learning without appropriate preprocessing. This section therefore investigates characteristics of syscalls, including the collection of syscall log data and properties of the data that enable the generation of a system behavior model.

3.1 Characteristics

Syscalls are used by almost all applications for communicating with and requesting services from the kernel of the operating system that the applications run on. Employing syscalls as an intermediary is thereby a necessary step to provide controlled access to security-critical system components. There usually exist hundreds of different available system calls in most modern operating systems, some of the most common being open, read, or exec (Mandal, 2018).

In busy systems, service requests to the kernel are frequent, which generates long sequences of syscalls. Theoretically, the possible amount of combinations of consecutive syscall types is immense; however, investigating syscalls shows that occurring syscall subsequences are highly regular and contain chains of repeating patterns. The reason for this is that applications execute the same machine code over and over, thereby generating similar syscall sequences multiple times. Moreover, the steps necessary for carrying out particular tasks are usually not subject to change over time, but are relatively constant (Forrest et al., 1996). Therefore, mining frequently occurring sequences allows to generate normal system behavior models.

Parameters of syscalls on the other hand are more variable than syscall types and usually depend on the elapsed time, user input, other processes, or the system environment. While this makes them considerably more difficult to analyze than just the sequences of syscall types alone, they express the purpose of the syscall in a more fine-grained detail and are thus able to reveal information on the context in which the syscall is executed (Liu et al., 2011). When this context is expanded to not just one, but sequences of syscalls, conclusions on the current state of the system with respect to all its active processes can be drawn.

Incorporating context is a key aspect for utilizing syscalls for security, since any attacks or exploits are highly likely to manipulate or spawn processes and thus manifest themselves within the syscall logs. Thereby, a single syscall instance alone may not necessarily be reasonably recognizable as part of a malicious process; but rather one or multiple syscalls that are executed within a specific context may be indicators that the system has been compromised.

Figure 1 shows a sample syscall log line from an Apache server. Since the syntax of the lines are known and only consist of key-value pairs, a parser is able to extract all relevant parameters from such a syscall log line, including the time stamp, CPU architecture (arch), syscall type, return values (success, exit), arguments (a0 to a3), user information (uid, gid), process information (pid, comm, exe), and several more. In addition, a number of PATH records may follow each syscall (indicated by items). It is usually not feasible and reasonable to include all parameters when generating self-organizing maps. The following section explains the difficulties and outlines a method for selecting suitable parameters.

3.2 Feature Selection

One important observation from the sample syscall log line shown in Fig. 1 is that all parameters (except the timestamp) should be treated as categorical variables, since it is not possible to establish proper ordinal relationships between the values, even though some of them are numeric. For example, syscall type 1 (write) is in no way closer related to syscall type 2 (open) than to syscall type 257 (openat).

One possibility to enforce correct handling of categorical features is to apply one-hot encoding (Harris and Harris, 2007) to the extracted parameters. For this, it is first necessary to identify all unique values of a parameter to be encoded. In the second step, the parameter is replaced with a range of parameters, where each of them specifies whether the respective value is present in the syscall log line (1) or not (0). Table 1 shows some encoded parameters of the sample log line from Fig. 1. Thereby, the original name of the parameter is specified before the underline character, followed by the value. In this sample, three syscall types (1, 2, 257) are present in the data, and accordingly three parameter-value pairs exist, of which the first one is set to 1 and all others to 0 corresponding to the syscall type 1 in the sample log line. This is carried out analogously for all other parameters. Note that for each set of parameter-value pairs, only a single 1 is allowed, since each parameter exists only once in each log line.

Unfortunately, parameters that contain only or high amounts of unique values result in a massive enlargement of the resulting feature vector, but only contribute little or nothing to the ability of grouping the syscall observations, because the values are almost always 0 for each observation. Simply omitting such parameters is not recommended, because there may be one or few values that occur more often than others, which can be relevant feature for clustering. For example, half of all syscall log lines could have argument a3=0, while all others have unique values for this parameter. We suggest to group all values with insufficiently high occurrence frequency in a single wildcard-bucket, e.g., all values of a feature that occur in less than 5% of all rows. This ensures that frequently occurring values relevant for clustering remain in the data, while at the same time vector dimension is kept within reasonable bounds. Table 1 shows this idea applied to the parameter exit, where all exit values other than -2, 0, 19 are allocated to exit_*. Syscalls in this vector format are suitable for training a SOM. The SOM training process is outlined in the following section.

4 SELF-ORGANIZING MAPS

This section covers the basics of self-organizing maps (Kohonen, 1982). We also mention differences to typical SOM applications and the role of SOMs in our approach.

4.1 Overview

A self-organizing map (SOM) is a type of neural network that supports unsupervised learning. The main goal is to visually represent high-dimensional input data within a low-dimensional (typically two-dimensional) space while maintaining topological properties as closely as possible. This is achieved by assimilating inherent structures of the input data by a set of nodes that are usually arranged within a rectangular or hexagonal grid of predefined size. Displaying the trained grid in a two-dimensional space is a useful tool for visualization.

The training procedure is as follows: a weight vector of the same dimension as the input data with initially random values is assigned to each node of the grid. The input vector of each syscall instance is then iteratively presented to the network, which learns structures of the input data by adjusting the weight vectors accordingly. Other than most existing neural networks, SOMs pursue competitive learning, meaning that for each syscall observation, the best matching unit (BMU) is selected by computing the minimal distance between the input vector and all of the weight vectors. Typical selections for the distance function are the Euclidean distance for continuous data and the Manhattan distance for binary or categorical data. The weight vector of the best matching unit is then modified to resemble the currently processed input vector more closely using a predefined learning rate. In addition, all neighboring nodes of the best matching unit are modified analogously, but to a lesser degree. This is carried out iteratively for all syscall observations in the input data and typically repeated several hundred times, until the weights of the grid reach stability (Kohonen, 1982).

As explained in Sect. 3.2, the approach proposed in this paper makes use of one-hot encoded input data in order to handle categorical values correctly. This binary data influences the typical outcome of the SOM: it is less common that input vectors fit “in-between” frequently hit nodes, i.e., relative to the size of the grid, only a small amount of nodes are selected as best matching units. This leads to the formation of relatively clear boundaries between the nodes, which is not usual when SOMs are trained with continuous ratio scales that typically result in smooth and gradually changing structures. Accordingly, the SOM functions more like a clustering algorithm that groups similar syscall log lines in the same nodes, but has the advantage to automatically determine the importance of each feature for each node and additionally maintains an overall topology useful for visualization.

4.2 Node Labels

Node labels improve the expressiveness and simplify interpretation of SOMs, because they represent the most important syscall properties and display which features are shared or differ between neighboring nodes. We therefore print the names of the most relevant features onto each node.

We mentioned that the binary input data affects the overall distribution of the nodes, but it also has an effect on their labels. Other than for continuous data where the feature weights of each node are not bounded, the weights in our setup lie within the range $[0,1]$. Given that the input vectors are high-dimensional, it is not unusual that several feature weights computed at some nodes reach the maximum value of 1, meaning that the corresponding features are all equally important for describing the node, making automatic selection difficult. In addition, since these weights are computed solely using the vector instances that are mapped to the respective nodes or their neighborhood as outlined in Sect. 4.1, they may not necessarily be appropriate to describe the node with respect to rest of the grid or the other data instances. For example, a feature that is 1 in every instance of the whole data set yields the same weight of 1 at every node as another feature that is 1 only in the instances mapped to a specific node, and 0 in all other instances. However, the latter feature describes what makes that specific node different from the rest of the grid and is thus an arguably more informative label for the node.

We propose to alleviate this issue as follows. For each node $n \in \mathbf{N}$, compute the relative amount of ones separately for every feature $n_1, n_2, ..., n_N$ considering all instances mapped to that node, i.e., $r_1, r_2, ..., r_N$ with $r_i = \sum n_i \div |n|$, where $|n|$ is the number of instances mapped to n. Then compute the relative amount of ones for every feature considering all instances that are not mapped to that node, i.e., use the rest of the instances from the whole data set $m = \mathbf{N} \setminus n$ to compute $s_1, s_2, ..., s_N$ by $s_i = \sum m_i \div |m|$. Finally, compute the vector $w = r - s$ that is higher for features that are present many times in the node instances, but rare in the data set. We see this value as a weight that indicates the most interesting features that distinguish the nodes and thus use it to select the labels.

Note that it is also possible to approach this issue conversely by considering the absence of a feature as an appropriate descriptor for a node. This is carried out in the same manner, but computing the relative amounts of zeros present in the data instances mapped on the node and the data set respectively. However, it is less intuitive to comprehend this kind of labeling and it was therefore omitted.

We also want to point out that due to the fact that the one-hot encoded data of one specific syscall log parameter always must only have a single 1 in all the features belonging to that parameter, it is unlikely that more than one feature corresponding to the same syscall log parameter are within the set of highest-weighted features. Considering the sample shown in Table 1, this means that it is unlikely that both features syscall_1 and syscall_2 are within the top ranked features, but rather a mixture of different parameters.

5 SYSTEM BEHAVIOR ANALYSIS

The previous section explained relevant properties of SOMs with respect to binary input data that is derived from syscall log lines. In this section we build upon these insights and propose concepts for deriving system behavior from the SOM.

5.1 Frequency Analysis

After training the SOM is completed, it is possible to map every syscall feature vector from the input data set to the node that yields the lowest distance to that input vector, analogously to the learning process described in Sect. 4.1. Visualizing these hit frequencies of all nodes results in a so-called hit histogram that displays the distribution of syscall execution frequency across the nodes. The hit distribution is relevant for system behavior analysis, because in steady systems the relative amounts of occurrences of all syscall types are normally expected to be quite stable within identically sized time windows, or follow periodic behavior.

We use logarithmic scaling for visualizing hit distributions. The reason for this is that in almost all real systems, syscall frequency distributions are highly unbalanced, making it difficult to recognize deviations on low-frequency nodes. An example of a hit histogram is given in the following section.

5.2 Sequence Mining

Hit histograms represent a static unordered view on the syscalls appearing within a time window and thus

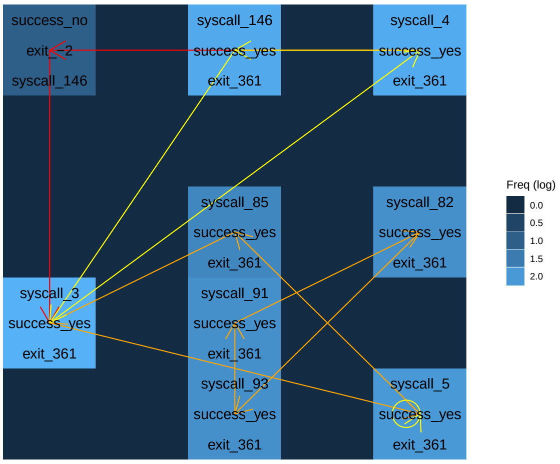


Figure 2: SOM of three sample processes (orange and yellow loops of arrows), including one anomaly (red arrows).

lack the ability to represent the sequences of syscalls. Our approach therefore connects nodes that are consecutively hit with arrows that point from each node to the subsequently hit node. When the same node is hit twice in a row, we insert a circular arrow pointing from the node to itself. We superimpose all arrows on the hit histogram and color the arrows according to the number of times this connection is present in the data, where yellow indicates a high number of transitions, orange indicates a moderate number of transitions, and red indicates a low number of transitions. Again, logarithmic scaling is applied.

Figure 2 shows a demonstration of the mentioned concepts on sample data. The data used for this visualization captures the three processes P1, P2, and P3 that continuously execute the following types of syscalls: P1 executes 93-91-82-93-91-82-..., P2 executes 3-4-146-3-4-146-..., and P3 executes 3-5-5-85-3-5-5-85-... over a long period of time, where each number corresponds to a particular syscall operation, such as opening a file or executing a task. Several conclusions can be drawn from the plot: First, all processes are correctly depicted. The smaller orange loop of arrows in the bottom right corner corresponds to P1, the yellow loop of arrows corresponds to P2, and the larger orange loop of arrows in the bottom corresponds to P3. It is easy to distinguish the processes by observing the node labels where the syscall type is placed as the most relevant characteristic of most nodes, because it is the most diverse feature in the data. Second, P2 contains an anomaly that manifests itself as a syscall of type 146 that returns an unsuccessful exit code -2 instead of the successful exit code 361. Such an anomaly could not be detected by a system behavior modeling approach that only takes syscall type numbers into account. Accordingly, the labels show that the parameters are higher weighted than the syscall type. Third, the hit histogram shows that the node of brightest color corresponds to syscall type 3, meaning that it is most frequently hit. This is reasonable, because both P2 and P3 make use of syscall type 3. Fourth, the arrow colors show that the yellow loop of transitions corresponding to P2 is the most active of all processes, and that the anomalous syscall was only executed very infrequently as indicated by the red arrows.

Note that processes usually overlap each other and are often executed in parallel. This causes that the sequences of syscalls are interleaved and thus lead to inconsistent transitions between the nodes. It is therefore necessary to only draw connections from any hit node to the subsequently hit node if the corresponding syscall logs originate from the same process. Luckily, syscall log lines typically have some kind of process identifier (e.g., the field pid logged by the Linux audit daemon) that allows to differentiate the individual processes easily.

5.3 System Monitoring

Utilizing these process identifiers allows to create process models within the SOMs by selecting only the syscall log lines that possess the respective identifier. However, this would result in numerous SOM visualizations that have to be tracked simultaneously. We therefore propose to superimpose the transitions identified from all processes onto a single SOM, despite the increased complexity of the resulting plot.

The purpose of the transitions is to incorporate temporal dependencies into the plot. However, a SOM is still a rather static construct; it captures the system behavior within a specific time window. In order to obtain a more dynamic view on the system behavior, our approach is to run a sliding window over the data to generate sequences of SOMs. By going through the SOMs of the time slices, changes of the system behavior, such as previously empty nodes popping up, transitions suddenly appearing, or frequencies rapidly changing, become more obvious for the analyst.

We support this visual analysis by automatically computing anomaly scores that describe the difference between two consecutive SOMs. We utilize two anomaly scores: (i) node-based anomaly score that is defined as the sum of squared differences of all node hit frequencies, and (ii) transition-based anomaly score that is defined as the sum of squared differences of all node transition frequencies. These anomaly scores form time-series, where low values indicate constant system behavior and rapidly increasing anomaly scores indicate a change of system behavior that may originate from malicious activity.

5.4 Syscall Aggregation

The methods outlined in the previous sections focus on mapping individual syscalls to SOMs, visualizing their interactions, and detecting changes of reoccurring behavior on a detailed level. However, it is not easy to differentiate individual states of the system behavior, for example, periodically reoccurring states or the return to a known anomalous state.

For such a broader view on the data, we visualize aggregated syscalls, i.e., occurrences counted within sliding time windows. Other than the frequency-based approaches mentioned in Sect. 2 that count only syscall types, we propose to take all syscall parameters into consideration. In particular, we compute the sum of occurrences of each feature in the one-hot encoded data. The resulting data matrix containing continuous values is then used as the input of a SOM. We then slide another fixed-size window over the data instances that represent aggregated time windows and create sequences of hit histograms. Since syscalls are not ordered in this setup, we omit displaying the transitions in this view. We present the resulting visualizations at the end of Sect. 6.4.

6 EXPERIMENTS

This section presents the experimental validation of our approach. We describe the input data and the generated SOMs.

6.1 Data

We validated our approach on real syscall log data that was generated by employing a modified version of the semi-supervised approach proposed by Skopik et al. (Skopik et al., 2014). Our system comprises a MySQL database and an Apache web server that hosts the MANTIS Bug Tracker System[1] and had virtual users perform normal tasks on the web interface, including reporting, editing, and viewing bugs, changing their preferences, etc. The syscall logs were collected using the audit daemon (auditd[2]) from the Linux Auditing System and a set of auditing rules that log the most relevant syscall types from all processes started by the Apache user. The sample syscall log line shown in Fig. 1 was generated on our system. In total, we obtained 70 unique types of input vectors after one-hot encoding.

The log lines were preprocessed using a Python script that extracts all values into a CSV format. We carried out our analyses in R, where we used the packages kohonen[3] for generating SOMs and ggplot2[4] for plotting.

6.2 Attacks

Beside visualizing normal system behavior in a SOM, we also pursued to validate the ability of our approach to visualize anomalies, i.e., deviations from the normal behavior, within a realistic scenario. For this, we set up exploits for five vulnerabilities on the Apache web server and prepared one vulnerability scan triggered by the same user that accesses the MANTIS Bug Tracker System for generating the normal data. The attacks comprise (i) a local file inclusion, where the content of a file locally stored on the Apache web server is accessed, (ii) a remote file inclusion, where content served by the web server is executed, (iii) a command injection, where user information is displayed by executing a command locally on the machine, (iv) a remote command injection, where netcat is used to execute a reverse shell, (v) an unrestricted file upload vulnerability, where a file can be placed into an arbitrary directory, and (vi) a vulnerability scan, where the Nikto Web Scanner[5] is used to generate suspicious user behavior.

We ran the simulation for a total of 320 minutes and directed the user to execute the attacks in the same order as described above in intervals of 50 minutes, starting at minute 30. The manifestations of these attacks in the syscall audit logs were afterwards manually located to verify their presence. Each attack generates a sequence of syscalls, of which most parts are identical to syscall sequences that correspond to normal behavior. Only some of the syscall log lines differ from normal behavior by their syscall types, parameters or place in the sequence.

6.3 System Behavior Model

Before going into detail on the detection of the attacks, we first investigate the visualization of normal system behavior. In order to display the normal behavior, the SOM is trained on the full data set,

[1] https://www.mantisbt.org/

[2] https://linux.die.net/man/8/auditd

[3] https://cran.r-project.org/web/packages/kohonen/index.html

[4] https://cran.r-project.org/web/packages/ggplot2/index.html

[5] https://cirt.net/Nikto2

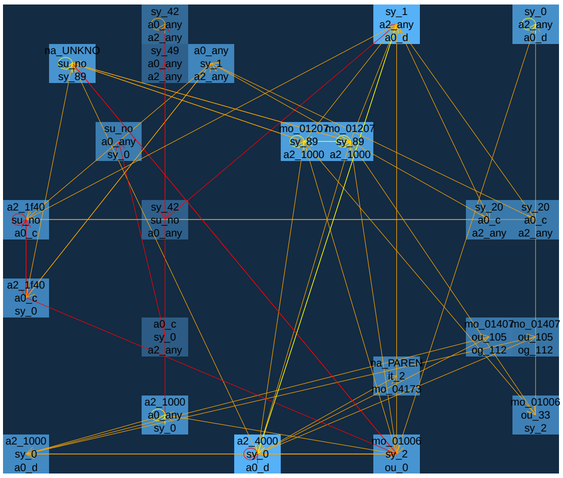


Figure 3: Visualization of syslog data representing normal behavior.

which also includes the log data corresponding to the attacks. Then, a sliding time window of 10 minutes passes with a step width of 1 minute over all syslog instances that occur before the first attack and maps these points into the SOM. Figure 3 shows one of these mappings. In the figure, some nodes are brighter than others, meaning that they are hit more frequently. Similarly, yellow arrows indicate a high number of transitions between the two connected nodes, while orange arrows indicate a moderate and red arrows a low amount of transitions.

Despite the figure appearing complex at first glance due to the many arrows overlapping, the total amount of arrows is comparatively low considering that transitions could exist between any of the 23 nodes active in this time window. In fact, the average amount of outgoing transitions from each active node is only 2.55. Comparing multiple visualizations of non-overlapping time windows also shows that their distributions of nodes and transitions is remarkably consistent over time. This indicates that SOMs are able to capture the normal system behavior correctly and enables the detection of anomalies as changes of the otherwise largely constant plot.

6.4 Anomaly Detection

As mentioned in the previous section, the log data generated by the attacks was included in the training input data. However, there does not exist a specific feature that differentiates between normal and anomalous input vectors as it is done in most supervised learning methods that train their models on labeled data. We therefore consider our proposed approach to be an unsupervised method to identify anomalous system behavior within a fixed set of input data that enables clustering and differentiation between normal behavior patterns and attack classes.

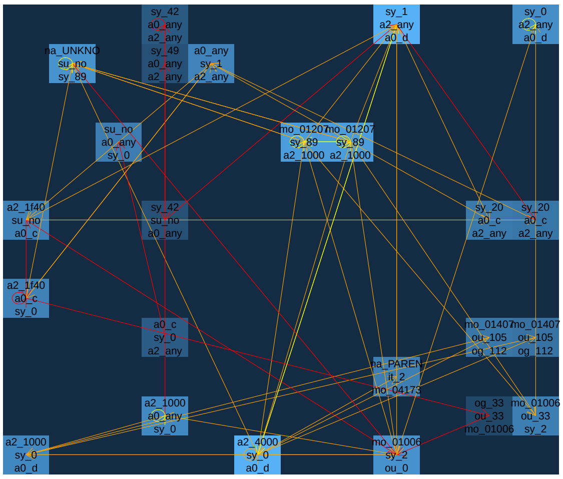


Figure 4: Visualization of the local file inclusion attack.

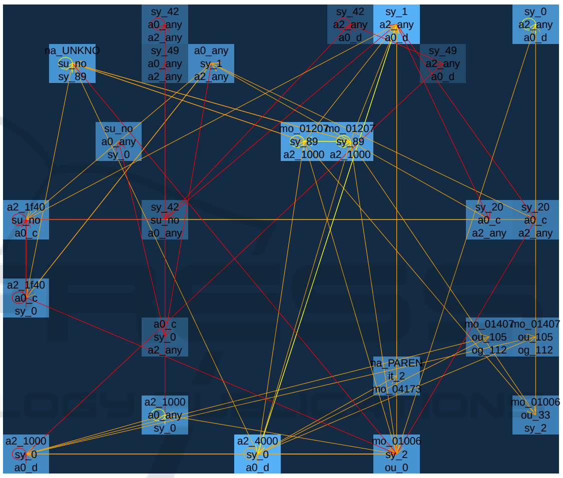


Figure 5: Visualization of the remote file inclusion attack.

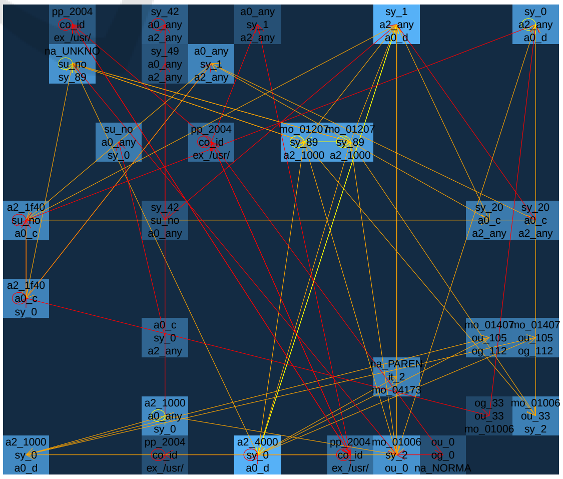


Figure 6: Visualization of the command injection attack.

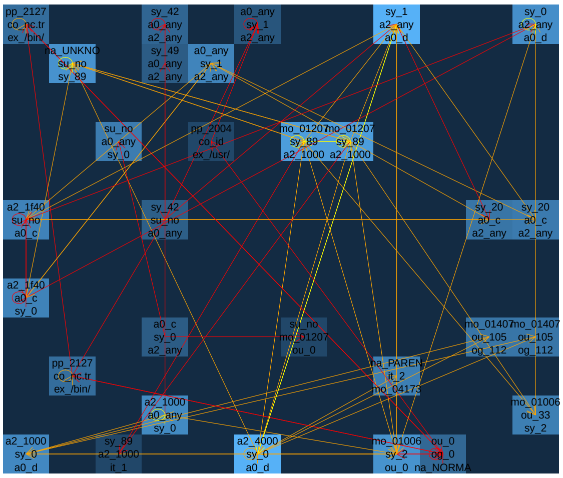


Figure 7: Visualization of the remote command injection attack.

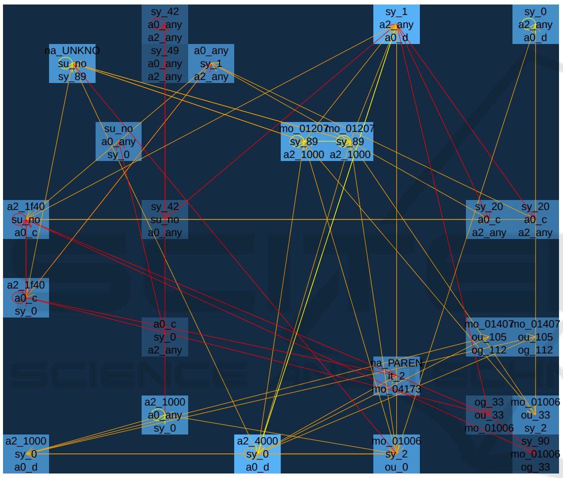


Figure 8: Visualization of the file upload injection scan.

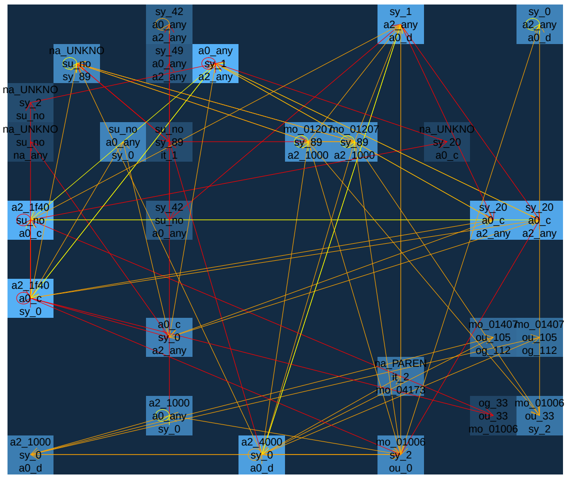


Figure 9: Visualization of the vulnerability scan.

We now go through the SOM visualizations that involve attacks. For this, the sliding window approach used to capture the normal system behavior was carried on to generate SOM mappings for time windows of 10 minutes length distributed over the whole data set. We compared the consecutive SOM visualizations to empirically assess that this time window size is large enough to record almost all normal behavior and small enough so that attacks do not overlap, i.e., there is always at most one attack taking place in every time window. Also note that the maximum delay between the launch of the attacks and their detection is equal to the step width of the sliding time window, i.e., in our setting, it takes at most 1 minute after completion of the attack to see its effects in the SOM. In the following, we select a representative time window for each attack and discuss whether and how the malicious behavior manifests itself as artifacts in the respective visualizations.

Figure 4 shows the visualization of the system behavior influenced by the local file inclusion attack. This attack only generates a single suspicious syscall log line and is thus the most difficult attack to detect for our SOM approach. Comparing the SOM mappings to the SOM that visualizes normal behavior, this log line manifests itself as one additional node hit that is visible close to the bottom right corner of the SOM. The labels suggest that ogid=33, ouid=33, and mode=0100644 are the most relevant features. We assessed that these feature values individually occur several thousand times in the data, but only their combined occurrence is distinctive for this and three other attacks. This shows that the attack is not detectable by monitoring all parameter values individually, but only the combinations of values.

As visible close to the top right corner of the SOM in Fig. 5, the remote file inclusion attack includes the execution of syscall types 42 and 49. Again, both these syscalls and the parameter a0=d are common in the data, but only their combined occurrences are unique for this attack. The command injection attack displayed in Fig. 6 is easier to detect, since it generates several unusually parameterized log lines, which are visible in the top and bottom of the SOM. In particular, the log lines stand out due to their parent process id (ppid) of 2004 and the command (comm) value “id”. A similar interpretation is possible for the remote command injection attack displayed in Fig. 7, with the difference that netcat (nc.traditional) is used as a command. Figure 8 shows the file upload injection attack, which causes the execution of the same command as the local file inclusion attack and additionally generates a syscall of type 90 that appears as a node hit in the bottom right of the SOM. This

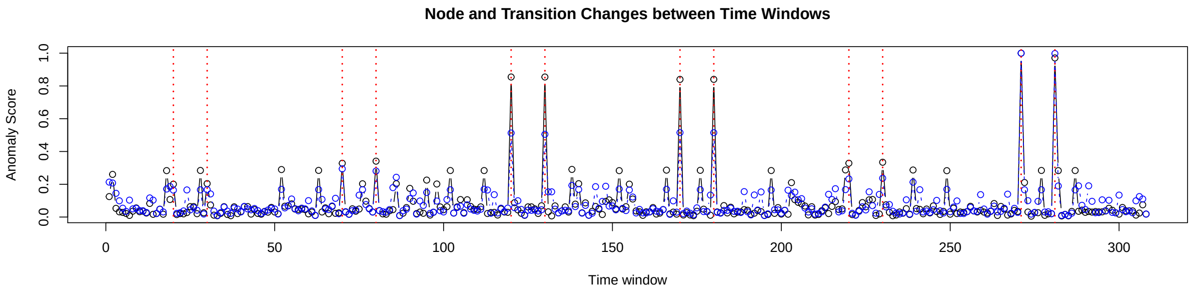


Figure 10: Anomaly scores computed from node (solid black line) and transition (dashed blue line) changes show rapid increases when the sliding time window enters and leaves intervals containing attacks (dotted red, vertical lines).

is the only syscall of this type in the data and thus also detectable without context information. Finally, Fig. 9 shows the SOM corresponding to the vulnerability scan. This attack induces the execution of several thousand syscalls and is thus the easiest of our attacks to detect. Beside some previously inactive nodes receiving hits, the attack mainly manifests itself as changes of hit and transition frequencies in the SOM, visible by nodes turning brighter and arrows changing color.

As outlined in Sect. 5.3, the differences between the consecutively generated SOMs result in time-series that indicate changes of system behavior. Figure 10 shows the progression of these anomaly scores measured on the nodes and transitions over time. Note that due to our sliding window approach, each attack causes a peak when the attack enters the window and another one when the attack leaves the window. The anomaly score does not indicate system behavior changes from time windows in-between, because they are all equally affected by the same attack. The dashed red lines mark the points in time where the change of system behavior is expected.

In alignment with the observed changes of the SOMs, the third, fourth and sixth attack are strongly visible as peaks of the anomaly score, the second and fifth attack cause moderate increases and the first attack slight increases of the anomaly score. The progression of the anomaly score also shows several smaller peaks that are dismissed as false positives. Closer inspection shows that most of them are indeed generated by inconsistent behavior of the web server, but do not relate to our injected attacks.

Finally, Fig. 11 shows the results of our experiments with aggregated syscall data as described in Sect. 5.4. We display twelve plots where attack and normal behavior phases are alternating, i.e., the plots in the first, third, and fifth column correspond to the six attacks, while the plots in the second, fourth, and sixth column correspond to phases of normal behavior in between. Note that each plot covers a time span of 35 minutes and consists of data points that represent 25 minute time windows, e.g., the first plot covers the time span of minute 7 to 42 and contains twelve data points corresponding to the sliding time windows 7-32 minutes, 8-33 minutes, ..., 18-43 minutes.

We interpret the plots as follows. Time windows of normal system behavior relate to nodes in the center or closer to the bottom left of the plot. Time windows that contain attacks end up concentrated on the sides or in the corners of the SOM. The reason for this is that these anomalous phases are highly different and thus end up far away from the normal behavior. The reason that the normal behavior does not perfectly overlap is attributable to the false positives already mentioned.

Note that we ascertained that the labels largely correspond to the labeling of the SOMs discussed before, i.e., nodes of SOM mappings of data containing attacks are labeled according to the respective features relevant for detection. For a more convenient view of the plots, we decided to cluster the nodes according to their distances using a hierarchical clustering algorithm. The clusters are displayed in Fig. 12 for a predefined amount of 6 clusters (left) and 13 clusters (right). Note that the cluster plot functions as a mask that classifies system behavior when being superimposed on the SOMs from Fig. 11. In particular, the left plot shows that clusters are found at the top left, top right, and bottom right corner as well as the right edge of the SOM, while the large gray area (marked with 1) mostly corresponds to normal behavior. The colored areas correspond to the third, fourth, fifth, and sixth attack, and thus confirm our interpretations of the SOMs. Note that the clusters 5 and 6 in the top right corner correspond to only one attack. The plot on the right shows that a more fine-grained clustering is required to also identify the first and second attack, which are more difficult to detect. However, this also misclassifies the normal behavior between the first and second attack.

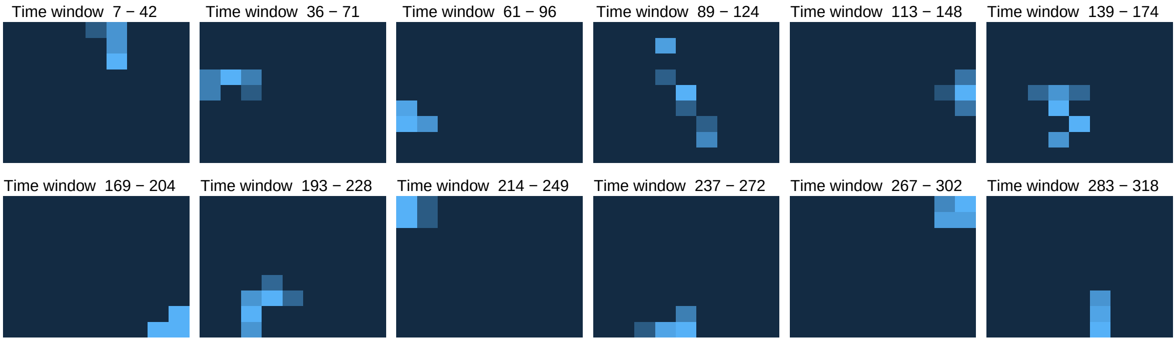
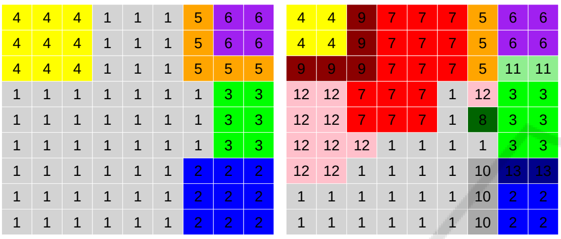


Figure 11: SOMs of aggregated syscall data from multiple time spans. The plots in the first, third, and fifth columns correspond to attack time windows, while the plots in the second, fourth, and sixth columns correspond to normal behavior in between.



4	4	4	1	1	1	5	6	6
4	4	4	1	1	1	5	6	6
4	4	4	1	1	1	5	5	5
1	1	1	1	1	1	1	3	3
1	1	1	1	1	1	1	3	3
1	1	1	1	1	1	1	3	3
1	1	1	1	1	1	2	2	2
1	1	1	1	1	1	2	2	2
1	1	1	1	1	1	2	2	2

4	4	9	7	7	7	5	6	6
4	4	9	7	7	7	5	6	6
9	9	9	7	7	7	5	11	11
12	12	7	7	7	1	12	3	3
12	12	7	7	7	1	8	3	3
12	12	12	1	1	1	1	3	3
12	12	1	1	1	1	10	13	13
1	1	1	1	1	1	10	2	2
1	1	1	1	1	1	10	2	2

Figure 12: Clusters serving as a mask for SOMs. Left: 6 clusters differentiate normal behavior (marked with 1) and four attack phases. Right: 13 clusters identify all attack phases.

7 DISCUSSION

The results presented in the previous section show that all injected attacks are detected by our approach. In particular, the labels of the nodes that correspond to the anomalies indicate that the parameters of the syscall log lines are essential in differentiating between normal and anomalous behavior. This is a significant advantage to existing methods that only focus on syscall types alone.

Employing SOMs for system behavior modeling emerged as a useful tool to generate visual assistance that improves the overview of the data and enables the exploratory detection of anomalous behavior. Thereby, no particular domain knowledge about the syscall log lines and the monitored system itself is required, as long as a reasonable time window size that captures all normal behavior is selected. We deliberately did not select a particular set of parameters for our analyses, but rather used all available values that occur sufficiently many times in the data, as outlined in Sect. 3.2. We realize that difficulties regarding the selection of appropriate time window sizes and thresholds for binning feature values may emerge in practical applications, but argue that they can be determined with reasonable effort during the exploratory analysis. Nevertheless, we are aware that an automated parameter selection is able to improve the method and support the analyst. We leave this task for future work.

Despite the fact that our feature selection combined with the one-hot encoding resulted in high-dimensional input vectors, we observed that the complexity of the data was rather low, consisting only of 70 unique types of input vectors. The reason for this is that our Apache server handles almost all operations made on the website similarly, despite random navigation and selections on the website. A system that produces more complex input data would require larger SOM sizes in order to decrease the chance of normal and attack input vectors being mapped to the same nodes. Choosing optimal SOM sizes and cutoff values for feature selection is non-trivial and must be determined iteratively by exploration. Note that we due to our exploratory approach, we did not carry out any evaluation regarding the computation time and focused on the detection and interpretation of patterns.

One limitation of our approach is that attack vectors must be present in the training data, otherwise the SOM does not learn the feature weights of the attacks, and mapping them to specific nodes is not possible. This prevents online detection of unknown anomalies on a pre-trained SOM. One solution is to continuously retrain a SOM on the most recent data for detection of unknown anomalies and use pre-trained SOMs only for classification of known attacks.

Furthermore, it is non-trivial to derive concise rules that describe system behavior from SOMs. This is due to the fact that the visualized processes frequently overlap partially and share nodes, making it difficult to extract dependencies.

Finally, the node placement of SOMs is topologically correct in the sense that similar syscalls are likely to be located close to each other. This makes it possible to easily recognize variations of existing sequences and determine which features are responsible for the divergences. However, the placement is almost certainly not ideal to visualize syscall sequences in chains, i.e., to reduce the arrow lengths between nodes. While it is possible to display the active nodes of a SOM and their transitions as a graph and reorder the nodes to avoid edges crossing over or running across the plot, this would undermine the topological node placement of the SOM.

We especially recommend our approach for systems with predictable behavior, otherwise the amount of false positives may easily become overwhelming.

8 CONCLUSION

In this paper, we introduced an approach to visualize high-dimensional syscall log lines using self-organizing maps. Other than most existing approaches, our solution incorporates parameters as context information, which is necessary to identify attacks that do not manifest themselves as anomalous sequences of syscall types, but rather involve unusual combinations of parameter values. Our visualizations involve hit histograms that show the number of input vectors mapped to each node, as well as transitions that display hit sequences. We used a sliding window approach to analyze consecutively generated SOMs and computed an anomaly score based on their pairwise changes. In addition, we proposed to aggregate the syscalls within time windows and also visualized their occurrence counts. We generated syscalls on a real system to validate our approach. All attacks injected in the system were identified as changes of the SOMs. We therefore conclude that SOMs are suitable to be applied for semi-automatic anomaly detection in fixed data sets by supporting exploratory analyses with visual cues.

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