Anomaly Detection Under a Cognitive Security Model

Detección de Anomalías Bajo un Modelo de Seguridad Cognitiva

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I. INTRODUCTION

The development of computer applications and emerging technologies, such as smart cities or industry 4.0, have optimized the technology services provided by organizations around the world. Additionally, the improvement of decision-making processes in real time has become a challenge for security managers. Furthermore, cyber security problems have been increasing constantly; attacks on system availability, information theft and loss of privacy have risen in recent years, according to the World Economic Forum [1].

In this context, the need to improve the cognitive skills of security analysts, and the use of technological tools to support cyber operations has increased. From our perspective, a direct relationship between the development of technological solutions and the skills of security analysts is important. Having an effective tool, but lacking a person capable of handling it, would limit the effectiveness of the use of the Elastic Stack (ELK). ELK is a set of tools that aim to help improve the indexation, searching and manipulation of the data [3]. In this study, we implement the ELK stack in order to index and analyze the data obtained from the IoT-23 dataset, which were downloaded directly from (4). This data is used in order to assess the connection and future development of a cognitive model, either supervised or unsupervised, which could be used to classify the data in a more reliable way. The results obtained showed a clear distinction between the behavior of malicious and the benign traffic, which facilitates the development of a future cognitive model based on the data.

II. THEORETICAL FOUNDATION

There are a set of security operational tasks that are developed daily by security analysts and that require the use of cognitive skills for their execution. These tasks were indicated by IBM at the RSA conference in 2017 [5]. On previous related work, we had grouped these tasks based on cognitive processes and the Observe-Orient- Decide-Act (OODA) cognitive model, proposed by Breton (See Table I, Table II and Table III) [6-7].

<table>
<thead>
<tr>
<th>TABLE I. OODA COGNITIVE PHASE AND COGNITIVE PROCESS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Process</td>
</tr>
<tr>
<td>Observe</td>
</tr>
<tr>
<td>Orient</td>
</tr>
<tr>
<td>Decide</td>
</tr>
</tbody>
</table>

The first two cognitive tasks “Review incident data” and “Review the events by aspect of interest” require the cognitive skill of perception by security analyst. The third task “Pivot in the data to find atypical values, or outliers” requires the cognitive process called comprehension. One of the daily operations carried out by security analysts, and related with these three tasks, is anomaly detection, i.e., the analyst's ability to identify outliers that could be possible security attacks, based on spikes in data traffic or by connections from uncommon services. This detection could allow cognitive security is considered as: the ability to generate cognition in order to take decisions effectively in real time, by either a human or a computational system. This ability is based on the perception generated by the system from its environment and the knowledge about itself, which is obtained from the analysis of any type of information, structured or unstructured, by using artificial intelligence techniques and data analysis. Therefore, the system can emulate the human thought process for continuous learning, decision making and, ultimately, security analysis.

Given the fact that we intend to work with enormous amounts of data, we propose the use of the Elastic Stack (ELK). ELK is a set of tools that aim to help improve the indexation, searching and manipulation of the data [3]. In this study, we implement the ELK stack in order to index and analyze the data obtained from the IoT-23 dataset, which were downloaded directly from (4). This data is used in order to assess the connection and future development of a cognitive model, either supervised or unsupervised, which could be used to classify the data in a more reliable way. The results obtained showed a clear distinction between the behavior of malicious and the benign traffic, which facilitates the development of a future cognitive model based on the data.

TABLE II. COGNITIVE PROCESS AND ITS ATTRIBUTES.

| Process | Attribute |
|----------------------------------------|
| Perception | Identification of relevant data |
| Comprehension | Interpretation of data |
| Projection | Prediction of future events |

The second two cognitive tasks “Review incident data” and “Review the events by aspect of interest” require the cognitive skill of perception by security analyst. The third task “Pivot in the data to find atypical values, or outliers” requires the cognitive process called comprehension. One of the daily operations carried out by security analysts, and related with these three tasks, is anomaly detection, i.e., the analyst's ability to identify outliers that could be possible security attacks, based on spikes in data traffic or by connections from uncommon services. This detection could allow
the security analyst to take the appropriate actions, and reduce the impact of the attack. Within cybersecurity, one of the concerns of security managers are anomalies, which are defined as the detection of surprising or unusual events [5]. There are several techniques to detect anomalies, which use a range of different methods, however, it should be considered that, when the malicious actions are caused by perpetrators, the abnormal observations tend to be adapted in order to appear normal. Another major problem is the availability of labeled data, which is needed for training and validating the computational models. To determine an anomaly, several factors should be considered such as: the nature of the input data (object, record, point, vector, pattern, event, case, sample, observation or entity), the availability or not of labels, as well as the limitations and requirements induced by the domain of the application [6].

Riveiro mentions a five-phase process related to the anomaly detection process [8]:
1. Overview: continuous traffic control in real-time.
2. Filter: define if something is abnormal (make a judgment based on their experiences).
3. Waiting Time: in which the event is observed in order to evaluate its behavior.
4. More detail: the situation is analyzed in more detail.
5. Taking-action: define the best responsive action.

The first step according to [8], is establishing the potentially dangerous situation, where the analyst should compare it, and update it, according to what would be the normal situation in the supervised zone. The second step correspond to narrowing the set of items, where the analyst zooms in and out the data to detect anomalous behavior, comparing it with real-time information. In this step, (8) suggests the use of data-mining techniques to decrease the time needed to identify anomalous situations. The third step is critical, because the analyst leaves the current traffic, in order to evaluate the status of the situation. This step is stressful for the analyst, due to the potential increase of traffic, or any impact in the services of the supervised zone. These three steps, defined by [8], require the analysts' cognitive processes, which we have grouped together in this work within the cognitive process called “perception.”

Increasing the analyst's cognitive skills can be carried out by several lines of action:

- Training,
- Experience gained from work,
- Technological solutions, or
- Cognitive security

TABLE III. COGNITIVE PROCESS RELATED TO CYBER-ATTACKS

<table>
<thead>
<tr>
<th>Cybersecurity operations tasks</th>
<th>Cognitive process</th>
</tr>
</thead>
<tbody>
<tr>
<td>Review incident data</td>
<td>Perception</td>
</tr>
<tr>
<td>Review the events by aspects of interest</td>
<td>Perception</td>
</tr>
<tr>
<td>Pivot the data to find atypical values or outlier</td>
<td>Comprehension</td>
</tr>
<tr>
<td>Expand the search to find more data</td>
<td>Projection</td>
</tr>
<tr>
<td>Investigate the truth to develop hypothesis</td>
<td>Comprehension</td>
</tr>
<tr>
<td>Discover new threats</td>
<td>Projection</td>
</tr>
<tr>
<td>Determine indicators of conspicuous in other source</td>
<td>Comprehension</td>
</tr>
<tr>
<td>Apply intelligence to investigate the incident</td>
<td>Projection</td>
</tr>
<tr>
<td>Discover potentially-infected PIs</td>
<td>Comprehension</td>
</tr>
<tr>
<td>Qualify the incident based on the knowledge generated while investigating the threat</td>
<td>Comprehension</td>
</tr>
<tr>
<td>Prescriptive analysis based on the profile of the attack</td>
<td>Comprehension</td>
</tr>
<tr>
<td>Analysis of the lessons learned, based on the dispersion map of the attack</td>
<td>Comprehension</td>
</tr>
</tbody>
</table>

III. ANOMALY DETECTION BASED ON COGNITIVE SECURITY

The objective of this work is to define the anomaly detection process by the security analyst, in order to translate it to a cognitive security model. The first cognitive process, used by an analyst for the detection, is the perception. The analyst must have the ability to detect outliers, by reviewing the data generated in the ecosystem. Based on the three steps proposed by [8], we propose in Figure 1, an anomaly detection process based in a cognitive model.

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1. Overview: continuous traffic control in real-time.
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of collected data, including their cleaning and profiling; therefore, is common in this type of process to select a methodology such as CRISP-DM, which is widely used in Data-Mining projects. In this study, we have established the premise that it is not feasible for the security analyst to have knowledge of all possible attacks, and that there are new attack vectors every day; the security analyst, therefore, starts from a state of uncertainty and lack of relevant information. From this point, the security analyst must build the necessary knowledge for decision making.

Regarding uncertainty, [15] mentions that uncertainty is a property of human in his/her mental processes. In this context, cognitive uncertainty is caused by the incompleteness of the important knowledge required (vague events), where fuzziness is also included as a type of non-statistical uncertainty. [15] also mentions that, categorization, is an essential function of the cognitive system when performing important processes, such as reasoning and problem solving. She proposes a reasoning and problem solving. She proposes a fuzzy membership function for categorization, where the function measures the degree of similarity of different objects. We can use fuzzy techniques to reduce the subjectivity of the security analysis. The fuzzy techniques could measure the relationship between two vague events: when an attack occurs (time), and the source of the attack (space). So, a fuzzy technique must be aligned with the temporal-spatial principle.

In the third step, there is a need to reduce the waiting time and select the best option, considering most of the possible scenarios. The use of Bayesian networks, with a cause-effect scheme, could support a security analyst in order to help him/her consider better alternatives. Additionally, Bayesian networks are effective while working with huge datasets, where spatial and temporal information might be included. Furthermore, the Integrated Nested Laplace Approximations (INLA) approach, is a computationally effective and an extremely powerful alternative to Monte Carlo (MCMC) methods.

The architecture, implemented for this study, is made up of three nodes. These 3 nodes have specific functions and will be known from now on as "collector", "index" and "reporter". The "collector" node has an Intel (R) Xeon (R) E5-2640 v4 2.40GHz processor, 4GB of DDR4 ECC memory and a 200GB NUTANIX VDISK disk. The "index" node has the same processor and memory characteristics, with the same disk model, but with 500GB capacity. Similarly, in the "reporter" node, there are the same characteristics in processor and memory, with storage of 100 GB. All three nodes are running the Ubuntu 18.04 LTR system. Additionally, all the nodes are connected through an Ethernet network, as shown in Figure 4, with a firewall that only allows the passage for port 22, to be able to connect using the SSH protocol. The functions of each node are differentiated for each of the components of the ELK stack. In this way, the "index" node is in charge of keeping ElasticSearch services running, indexing the data and searching for them. The "collector" node is in charge of separating, organizing and coding the information for its correct indexing within the "index" node. Finally, the "reporter" node is in charge of keeping the Kibana service running, to allow access and corresponding visualization of the data that are indexed in ElasticSearch. This node is in charge of maintaining a cache with the data that need to be shown in each query, in order to facilitate viewing and searching in real time.

To allow the visualization of the Kibana service from a computer external to the network, the "reporter" node has been provided with a public IP address, where the ports 80 and 443 are open to receive requests. The aforementioned ports are routed through a proxy, implementing the HTTP protocol, which allows us to redirect incoming traffic to the corresponding Kibana port. This port (5600) has been arbitrarily chosen for communication; the default port (5601) would also have the same functionalities.

The Logstash 7.9.0 service was installed according to the steps indicated in [19]. Similarly, a Debian package was used, which was downloaded from the Elastic servers. Once Kibana was installed, the elasticsearch.yml file was configured, which is located in the /etc/kibana folder. The options configured in this file were: the server port, the port where the file was opened, the elasticsearch listening port, the existing username for "kibana" for elasticsearch and the password that was configured in a previous step. The Kibana service was started, and kept running in background mode.

Additionally, Logstash was configured using the "integer" using the "mutate"

**IV. EXPERIMENTATION**

Los algoritmos de OCR permiten convertir texto en una imagen a caracteres (códigos de 8 bits, como los representados en tablas ASCII). El motor OCR adoptado fue Tesseract OCR.

**A. Configuration**

**index node**

In the "index" node, Elasticsearch 7.9.0 was installed as indicated in [16], through a Debian package, which was downloaded directly from the Elastic servers. Once the node was installed, we proceeded to configure the elasticsearch.yml file, which is located in the /etc/elasticsearch directory. In this file, the name of the cluster, the name of the node, the address for the data, the address for the records and the port where it will receive HTTP requests were configured. Additionally, x-pack was configured, following the steps indicated in [17]. For this purpose, the variable xpack.security.enabl

**Collector Node**

Logstash 7.9.0 service was installed in the "collector" node, following the steps specified in [19]. Additionally, the translate plugin was used to transform the log files, which were given in the file. Next, the Grok plugin was used to filter the rows and separate the data into the corresponding attributes, assigning each attribute the corresponding value as indicated in the header of the log file. This Grok filter was tested using the filter test function that is available among the Kibana plugins. Additionally, the "translate" plugin was used to obtain an additional attribute, which better explains the connection status from the nodes that are given in the file. Later, making use of several conditionals, the values of were replaced in the following attributes: id, orig_p, id, orig_ip_bytes, resp_bytes, missed_bytes, orig_p, orig_ip_bytes, resp_p, resp_ip_bytes and duration. Additionally, the integers were converted to "integer" using the "mutate"
be used for the creation of the index was indicated, specifying its name and that it should not be overwritten. In this template, which is structured as indicated in [23], we proceeded to specify the “mapping” of the index fields. This mapping was used to specify the data type for all the values that were previously encoded in numeric format. The Logstash service was then started using the “sudo systemctl start logstash” command, to run in background mode. Finally, the index was modified through the Elasticsearch API to reduce the number of replicas to zero, because there is only one node working with Elasticsearch and there is no possibility of implementing replicas of it.

V. RESULTS AND DISCUSSION

Once the data had finished loading into the index, an Index Pattern was created in Elasticsearch from Kibana. This pattern was used to verify the loaded data. As can be seen in Figure 5, the loaded data has been correctly indexed, with the format established in the template that was previously defined. With this Index Pattern, a dashboard was created, allowing a clearer view of the data that was indexed. To create the dashboard, the Kibana tool was used, and six visualizations were obtained.

Figure 7, allows us to appreciate the ports at which the malicious traffic is being directed. As it can be seen, the traffic tends to attack specific ports of some well-known protocols, such as telnet and HTTP. This is obviously done, in order to try to obtain access via these ports since they tend to be open in most cases. In contrast, in Figure 8, a huge difference can be seen in the ports that are being targeted by the benign traffic. Since this traffic has legitimate petitions, that are used to perform communications between the IoT devices, this clear difference was expected to be seen, according to the type of traffic.

The data obtained from the IoT dataset have allowed us to appreciate the differences between the behavior of benign and malicious traffic more easily. As it was previously seen, the differences in the traffic is clear enough to perform a detection by a security analyst only by visualizing the behavior of the data. Based on this principle, a Bayesian Network could be developed in order to detect the anomalies in the traffic. One of the obvious rules that could be used, would be a detection based on the size of the petition, relative to the size of the answer, in order to detect a possible attack that tries to gather information of the system.

Figure 9 shows the capabilities of ELK to display an anomaly timeline, created in base of multiple metrics. For instance, count of events versus IP address. This figure is also allowing us to identify the time of a day at which an anomaly is more likely to appear. Therefore, a system could be deployed to alert analysts of incoming traffic during those specific times of the day. The analyst could, consequently, prepare itself for a more focused and intensive analysis of the incoming traffic, since it has a higher probability of being a possible threat, due to the time of the day at which it is currently being performed. Additionally, the data clearly shows a difference in the ports that are being targeted by the malicious traffic, compared to the ports targeted by benign traffic. This difference is so prevalent that most security analysts already know which ports need to be secured, since those ports are more likely to be the target for future attacks. This data, therefore, allow analysts to protect the most vulnerable parts, and prevent them for the future, in order to focus their attention in the most vulnerable parts of the system.
VI. CONCLUSION

Currently, not only computers generate data, but people generate an additional challenge by having objects connected to the internet, such as sensors and appliances (televisions, refrigerators or cars), which are capable of generating data.

The substantial difference from our point of view of cognitive security as a cybersecurity strategy, versus other strategies, is the augmentation made by the analyst's cognitive skills. Coupling technological and data science solutions, to the cognitive process can generate a bidirectional contribution to the technological tool or algorithm, because it can be better trained and configured. Additionally, the analyst also obtains a bidirectional contribution, because they will get support in the development of their own operational tasks.

The efficiency at executing tasks in cybersecurity, depends of the cognitive processes of a security analyst. Additionally, the detection of anomalies also requires a cognitive process, and its effectiveness depends mostly on the degree of expertise that the analyst has. In this study, we have tried to highlight the importance of spatial-temporal reasoning, as one of the cognitive skills that must be developed by analysts to improve the anomaly detection processes.

Based on the spatial-temporal reasoning, we have proposed the use of data science algorithms such as unsupervised machine learning algorithms, fuzzy techniques and Bayesian networks, which can improve anomaly detection processes. In this study we wanted to highlight the importance of cognitive security, by integrating the point of view of the analyst’s cognitive processes with the technological and analytical solutions available to support them. The ELK stack has great capabilities for the analysis and indexing of data. In addition, it allows searching and storing data very easily, and has enormous possibilities for the visualization of large amounts of data. The use of this stack for the analysis of traffic data in IoT devices, has allowed us to improve the visualization of a huge number of records in a very fast time. The Kibana tool has great capabilities, which can be used to display large amounts of data in an intuitive way; with this tool, it has been possible to create visualizations with great potential, and that take very little time to update, thanks to the optimized operations performed in the indexes at Elasticsearch. Additionally, the implementation of Logstash increases the capabilities of the ELK stack, by allowing it to perform the indexing of the data in a simple way. Logstash functions to perform the reading, filtering and writing of information, allow the processing of any type of record easily and quickly. Finally, the use of the Grok plugin for structuring previously unstructured files, is the main tool that allows encoding and organizing the information in the formats.

Future works on this field could be focused in the development of an automated system, which would use the data collected for this study to train an unsupervised anomaly detection algorithm. This algorithm could use various techniques, including Isolation Forest. Clustering and Histogram based algorithms to perform an automatic detection, in order to help aid the security analyst in his work. Additionally, the relative simplicity of the previously mentioned algorithms during the deployment phase, will make it easy to perform real time intrusion detection, without causing any significant system. Therefore, an automated system deployed to perform anomaly detection will efficiently use the resources and, hopefully, reduce the workload of a security analyst in a significant manner, without losing efficiency in detecting possible intrusions.

VII. REFERENCES


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