Multi-Stage Attack Detection via Kill Chain State Machines

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ABSTRACT

Today, human security analysts collapse under the sheer volume of alerts they have to triage during investigations. The inability to cope with this load, coupled with a high false positive rate of alerts, creates alert fatigue. This results in failure to detect complex attacks, such as advanced persistent threats (APTs), because they manifest over long time frames and attackers tread carefully to evade detection mechanisms. In this paper, we contribute a new method to synthesize attack graphs from state machines. We use the network direction to derive potential attack stages from single and meta-alerts and model resulting attack scenarios in a kill chain state machine (KCSM). Our algorithm yields a graphical summary of the attack, APT scenario graphs, where nodes represent involved hosts and edges infection activity. We evaluate the feasibility of our approach in multiple experiments based on the CSE-CIC-IDS2018 data set [21]. We obtain up to 446 458 singleton alerts that our algorithm condenses into 700 APT scenario graphs resulting in a reduction of up to three orders of magnitude. This reduction makes it feasible for human analysts to effectively triage potential incidents. An evaluation on the same data set, in which we embedded a synthetic yet realistic APT campaign, supports the applicability of our approach of detecting and contextualizing complex attacks. The APT scenario graphs constructed by our algorithm correctly link large parts of the APT campaign and present a coherent view to support the human analyst in further analyses.

CCS CONCEPTS

- Security and privacy → Intrusion detection systems; Network security.

1 INTRODUCTION

The proliferation of security monitoring and mainstream adoption of intrusion detection systems (IDS) has shifted the bottleneck during incident response from a lack of visibility to a lack of human analysis capacity. The massive volume of incoming alerts overwhelms security teams, who already struggle from chronic understaffing. Coupled with a high false positive rate, alert fatigue creeps into daily operations and operators can no longer effectively separate the signal from the noise. Especially complex long-running attacks conducted by skilled attackers, also referred to as advanced persistent threats (APT) might remain undetected. This is a major problem because these attacks typically inflict financial damage in the double-digit million dollars [1]. A central research question must therefore lie in developing understanding and mechanism to detect security incidents before they turn into a major breach.

Numerous approaches to model attack behavior of multi-stage attacks exist in the literature [10, 11, 22]. The unified kill chain (UKC) [19] evolved as the most comprehensive and prominent model to differentiate individual APT stages. However, to the best of our knowledge, there is no approach that fully implements this model nor any of its predecessors like the intrusion kill chain (IKC) [11]. Existing approaches either just detect a single stage or only some connected stages, so that complex attacks cannot be fully detected. Furthermore, the spatial and temporal distribution of alerts related to complex attacks impedes their detection via conventional intrusion detection methods that usually operate in a batch-based fashion.

In this paper, we propose a new approach to make alerts more actionable, so that analysts spend less time triaging. We do so by first using an established alert correlation approach to preprocess the alert corpus into clustered meta-alerts and unclustered alerts. Next, we leverage the network direction to assign potential attack stages to all alerts and meta-alerts. Using further correlation and contextualization based on a kill chain state machine (KCSM) we synthesize APT scenario graphs that describe the individual steps of the multi-stage attack at the machine boundary. A unique feature of our approach is the use of topology information to contextualize the analysis. The typical segmentation of a network into zones makes it possible to infer directionality in the communication and enrich alerts with this information to infer potential attack stages according to the KCSM. In the next step we connect the alerts based on these potential stages in a graph and detect paths that resemble valid transitions according to the ordering of kill chain states in the KCSM. Ultimately, we obtain scenario graphs that provide the much-needed reduction of the original alert set and offer additional context about the potential APT campaign to the human analyst.

Our end-to-end prototype first distills raw network traffic into detailed protocol summaries with the Zeek IDS [18] and then uses graph-based alert correlation (GAC) [9] to obtain higher-level alerts. These alerts are processed in batches by our Killchain-based APT contextualization to construct attack scenario graphs by maintaining a resource-efficient and compressed representation of all prior batches and their alerts. This allows also to detect long-running APT attacks without the need to process all alerts at once together.
We evaluate our prototype on realistic data in two different ways. First, we apply it to the raw CSE-CIC-IDS2018 data set [21], where our approach yields a two orders of magnitude reduction in alert volume from 446 458 alerts to 700 scenario graphs. In the absence of ground truth, we have to classify them as false positives. We then inject a real-world multi-stage attack spanning ten days into the data set and demonstrate that our algorithm identifies the attack among 686 generated scenario graphs or 68.6 scenarios per day. For high-security environments like a government or critical infrastructure this number should already be manageable by human analysts. Furthermore, the set of resulting scenarios can be prioritized or filtered e.g., if critical hosts are involved or additional unrelated indicators of compromise are available.

The remainder of this paper is structured as follows. We review in Section 2 related work on alert correlation, APT models, and model-based APT detection mechanisms. In Section 3 we describe two variations of the kill chain state machine (KCSM) and our approach to contextualize multi-stage attacks based on it. We evaluate our approach in Section 4 with respect to accuracy and performance, and outline how KCSM supports real-world incident response scenarios. In Section 5 we conclude with a summary and an outlook.

2 RELATED WORK

2.1 Alert Correlation and Volume Reduction

Julisch proposes to cluster alerts according to their root cause [12]. However, root causes cannot be exactly determined and must be approximated. Therefore, alerts are grouped based on attribute similarity, which is also known as attribute oriented induction (AoI). Zhou et al. propose a different similarity-based clustering approach [26]. They leverage alert attributes as well, but matching attribute sets are predefined in lattice structures. Though highly efficient, this approach is limited to a priori known patterns. Zhang et al. propose a clustering strategy based on rough sets [24]. A projection function determines alert equivalence, instead of comparing alert attributes directly. Alert projections are correlated when they exhibit a certain timely proximity. Another noteworthy clustering strategy is based on alert entropy [8]. The authors observe that more frequent events carry lesser information than infrequent events. Partial entropy is used to identify alert groups with similar information content.

Each of these clustering approaches identifies attacks as a group of alerts. However, long running and stealthy attacks may not be represented as a group of alerts. Existing approaches operate on batches or temporal proximity of events. Depending on batch size, temporal dispersion of related alerts, and other factors, these approaches may struggle to correctly correlate alerts that belong to the extensive attacks often present in APT scenarios.

2.2 Attack Story Reconstruction

Most alert clustering approaches for reconstruction of attack stories operate in at least two steps: identify individual attack steps and then connect the steps for a holistic view on an attack scenario. Strategies for the second step differ with each approach, ranging from causal connections [16, 17], to mathematical, or graph-based strategies [5, 7].

2.3 APT Models

Many models have been proposed to describe multi-stage attacks in general and APT specifically. Most of them are based on the notion of a chaining of certain attack stages. Researchers of Lockheed Martin coined the term of an intrusion kill chain (IKC) [11]. The model separates an APT into seven distinct phases: reconnaissance, weaponization, delivery, exploitation, installation, command & control and actions on objectives. The IKC model is widely accepted and serves as basis for many model-based detection approaches [2, 20, 25]. Variations of the IKC exist for different areas of computer science. For example, Hahn et al. proposed some modifications to the IKC, such that it can be adopted to cyber physical systems [10].

Other attack chain models are based on the analysis of disclosed real-world APT attack reports and white papers. Following this approach, Siddiqi et al. [22] and Li et al. [13] present models with data exfiltration as the overarching goal. In another analysis Ussath et al. [23] find that attackers often use standard tools and old vulnerabilities (“living off the land”) while they rarely craft sophisticated exploits. Their attack chain model only considers actions on the victim and does not contain any objectives nor a reconnaissance phase. All these models are limited to the attacker behavior that was observed in the analyzed reports. None of these models account for attacker intentions like data corruption or manipulation of service behavior.

Daneshgar and Abbaspour present such a two-fold scenario reconstruction [6]. IDS alerts are clustered to identify attacks. The clustering step considers conventional attribute similarity together with a fuzzy, causal relationship indicator called correlation strength. Lastly, the system incorporates timely proximity of alerts before clustering. In a second step, the authors use a fuzzy variation of frequent pattern mining to interconnect these extracted attack steps. Similarly, Haas and Fischer detect multi-step attacks by first clustering alerts and then interconnecting those clusters [9]. The initial clustering is based on partial alert attribute similarity. As with many clustering approaches, the authors use a configurable minimum cluster size to discard non-relevant alert groups.

Many multi-stage attack correlation approaches exhibit the same general problem as pure alert clustering approaches. Most research focuses on the second step for attack interconnection. However, the first step for attack identification often uses some sort of alert clustering and hence faces the same limitations for long-running, stealthy attacks.
2.4 APT Detection

APT detection approaches can be divided in two major areas: First, there are approaches that emphasize a single APT stage and focus on the detection of that particular stage. The existence of an APT attack is expected when the stage is detected. Second, there are approaches that attempt to detect and connect multiple stages of an APT model to obtain a more comprehensive view on the attack.

Bortolameotti et al. proposed a system called DECANTeR [3] and introduce the idea of application fingerprinting. A normality model is trained that correlates applications with their usual HTTP requests. DECANTeR does not require any knowledge about malware and the generated model is solely based on benign network data. This becomes a drawback when the training data already contains malware traffic. Furthermore, installing new applications like a different browser requires to re-train DECANTeR.

Bhatt et al. present a framework that incorporates various data sources like IDS or firewall alerts and host or email logs [2]. Their approach uses assumptions on attacker behavior to map detected attacks to stages in the IKS model. Similarly, AUSPEX [15] incorporates logs from many sources. The authors focus on the detection of C&C, lateral movement, and data exfiltration because these stages exhibit a notable network and host footprint. The framework produces a ranked list of suspicious hosts to ease the work of analysts.

Generally, the multi-stage contextualization approaches are quite accurate when it comes to the detection and connection of attack stages. However, they mostly lack the ability to cope with slow and stealthy attacks. Some approaches have issues to scale along with the amount of monitored data, in particular those approaches that leverage host monitoring and logs.

3 MULTI-STAGE ATTACK DETECTION VIA KILL CHAIN STATE MACHINES

This section describes our approach for multi-stage attack detection that is summarized in Fig. 1. We first apply alert correlation to preprocess alerts into clustered meta-alerts and unclustered single alerts. Next, we feed both types of alerts to our APT detection and contextualization approach. We assign potential attack stages to alerts and link subsequent stages according to our kill chain state machine (KCSM) to generate APT scenario graphs. These scenarios reveal potential multi-stage attacks present in the alert data and aid the human analyst during incident triage and mitigation. The remainder of this section is structured as follows. In Section 3.1 we describe two variants of a KCSM that we derived from the unified kill chain (UKC) [19]. Our formalization makes the existing model more actionable and lays the groundwork for our approach. Next, we describe our algorithm to characterize and detect multi-stage attacks in Section 3.2. We show how potential attack stages can be derived from single alerts and meta-alerts and leverage the state machine to connect these attack stages to expressive APT scenario graphs.

3.1 Kill Chain state machine (KCSM)

A segregation of a network into multiple network zones, which is standard in security-sensitive organizations, forces an APT actor to follow a kill chain model [2]. The unified kill chain (UKC) [19] is the most comprehensive model we could find in related work and was thus chosen as basis for our approach. To make the model actionable for our algorithms, we formalized it to a state machine that we describe next. The original UKC involves 18 stages (c.f.: [19]).

Generally, each APT attack is unique. Some stages might occur repeatedly, others might be left out. Nonetheless, there is a certain ordering of attack stages that cannot be changed. For example, malware Delivery necessarily comes before Command & Control (C&C) or Lateral Movement (LM). Likewise, some stages might reoccur. When a network zone is Pivoted and new hosts are infected, C&C and LM might be observed repeatedly. We formalized the entirety of connections and conditions as a finite-state machine in Fig. 2a that we call the kill chain state machine (KCSM). We map APT stages to transitions as they represent attacker actions. States in KCSM represent the campaign progress with "Target selected" as the common start state. As the goals of APT campaigns can be quite diverse from espionage to manipulation and data theft, the end state is abstractly labeled "Goal". Overall, both states and transitions are divided into four major categories:

(1) Outside of target organization: States and transitions in this category can usually not be detected or require massive effort as the attackers do not interfere with the target network yet.
(2) General target infection: This category encompasses all states and transitions related to the infection of new hosts in already breached zones. Efficient detection usually requires a mixture of host and network information.
(3) New network zone breached: States and transitions in this category describe the attacker’s progress towards new network zones which are not yet discovered. Detection of actions in this category can largely be achieved via network data analysis as most operations involve movement between hosts.
(4) Campaign goals: This category of states and transitions is highly abstract as it is usually unknown what goals the campaign aims to fulfill. Detection is therefore also difficult with 4.4 Exfiltration as the only clearly defined transition.

Outside of target organization (purple). An APT campaign starts when the attacker has selected a target. 1.1 Reconnaisance follows to determine possible attack vectors and to choose an attack strategy. The attack is tailored to the target and malware is 1.2 Weaponized with an exploitable bug.

General target infection (orange). Once the APT actors are ready to act, they 2.1 Deliver the weapon to the target, e.g., a malicious Dropbox implant or a water-holed web server. The next goal is to get the delivered weapon executed in the target network. Therefore, tactics like 2.2 Social Engineering might be employed. After the initial 2.3 Exploitation, KCSM reaches the central state of infection.
From here on, all further APT actions take place inside the target’s infrastructure. The central state of “Infected” allows an APT to take various paths. Colors in KCSM states indicate different action paths that can be pursued. The states for infection and persistence are marked orange. Whenever a new box is infected, malware may be 2.6 Persisted and 2.7 Defense Evasion techniques are applied. It is possible to take actions in form of 2.5 C&C and 2.4 Lateral Movement (LM), just circling in the infected state. LM is considered the movement to a known target. Identifying new targets, however, falls into the third category.

Breaching of new network zones (green). An APT might need to 3.1 Pivot from an infected box or might already be in a position where it is worthy to start 3.2 Discovery. The 3.2 Discovery action is similar to 1.1 Reconnaissance but is conducted in the internal networks of an organization. Thereafter, the zone is known. Once the attacker 3.3 Escalates Privileges, they may 3.5 Access Credentials to gain network-wide permissions. After that 2.4 LM is possible within the new network zone, which brings the attacker back to the general state of infection. Note that KCSM makes the entire process of network zone breaching an optional path. Controlling the infection or spreading it to new machines, is always possible via taking the circular 2.4 LM and 2.5 C&C transitions in the “Infected” state. However, this path would presume that the attacker possess comprehensive knowledge of the network.

Campaign goals (red). The last category of states marks the path for acting towards objectives. From the state of infection, the attacker can reach a predominant network position or even directly proceed to the campaign goal. These unlabeled transitions indicate that APT campaign goals can be highly diverse. It is not required for an APT to 4.1 Collect or 4.3 Manipulate data. Similarly, 4.4 Exfiltration is not required to happen. However, in case data is exfiltrated, the attacker is required to collect the targeted data first. The unlabeled backwards transition from “Goal” to “Infected” state symbolizes how APTs remain in a system as long as possible. Acting on objectives, exploring new network zones, controlling and spreading are not necessarily bound to ever finish. It is important to note that we can differentiate the APT stages between stages that compromise new hosts and others that do not. The simplest example for the first category would be 1.3 Delivery or 3.1 Pivoting while 2.5 Command & Control or 4.4 Exfiltration do not compromise new hosts. We will use this information later in the contextualization approach to improve the results.

Network kill chain state machine (NKCSM). APT stages can be observed in many parts of a compromised network. 2.1 Delivery can happen via the network in the form of an email or offline via an infected thumb drive. 2.3 Exploitation or 3.3 Privilege Escalation are solely host-level activities and 3.1 Pivoting is often both a network and a host action. Monitoring the entire network of an organization is expensive. But monitoring every individual device of an organization is almost impossible [14]. With a network IDS like Zeek [18] it is possible to monitor the network traffic even of large networks with little administrative overhead. In contrast, collecting, shipping, and unifying traces from thousands of heterogeneous system components is more challenging. Interestingly, about half of the state transitions (and thus APT stages) might be observable on network level. The other half of all transitions may be observed on host level or even outside of the organizations scope. To highlight this, we present the network kill chain state machine (NKCSM) in Fig. 2b, a version of KCSM reduced to all stages that might be detectable at the network level. NKCSM keeps the start and end states from the original state machine (Target Selected and Goal). APT stages that either occur outside of the target’s network (1.2 Weaponization, 2.1 Social Engineering) or on host level (2.3 Exploitation, 3.3 Privilege Escalation, 3.4 Execution, 3.5 Credential Access, 2.6 Persistence, 2.7 Defense Evasion, 4.1 Collection and 4.3 Target Manipulation) are excluded. This reduces the total number of states from thirteen to six, while preserving core semantics of KCSM. The numbering of APT stages is preserved for simplicity. The general progression from initial infection over optional lateral movement and zone breaching to action on objectives is still present in NKCSM. However, all remaining transitions are network-based and thus potentially observable via a network-based IDS.

Figure 2: Two APT state machines derived from the 18 stages described in the unified kill chain (UKC). [19]
Table 1: Network-visible stages of an APT attack. The stage abbreviations are used throughout the paper.

| Full Name          | Abbr. | Network direction |
|--------------------|-------|-------------------|
| Reconnaissance     | R     | \( Z_0 \rightarrow Z_i \) |
| Delivery           | D1    | \( Z_0 \rightarrow Z_i \) |
| Delivery (2nd stage DL) | D2   | \( Z_i \rightarrow Z_0 \) |
| C&C                | C     | \( Z_i \rightarrow Z_0 \) |
| Lateral Movement   | L     | \( Z_i \rightarrow Z_j \) |
| Discovery ("Scan") | S     | \( Z_i \rightarrow Z_j \) |
| Pivoting           | P     | \( Z_i \rightarrow Z_j, i \neq j \) |
| Exfiltration       | E     | \( Z_i \rightarrow Z_0 \) |
| Objectives         | O     | \( Z_i \rightarrow Z_j \) |

3.2 APT Detection & Contextualization

The states and transitions formalized in the NKCSM can now be used to derive potential APT stages. Looking back at the NKCSM, we quickly realize that all APT stages still present in the network can be characterized by movement between specific network zones. Thus, we can use the network direction of an alert to derive potential attack stages it can represent. We define the network direction of a (meta-)alert to be the transition between the network zones of the source and destination of the alert. A network zone describes one or more subnets of the same trust level. Examples of typical network zones in an enterprise network are external, intranet, datacenter, and dmz. Given the topology information of the target network, we can assign the network direction for any network-based alert. This makes our approach extremely flexible as it does not require special stage information in our source alerts.

**Attack stage assignment**. Table 1 shows which network directions are found in each stage of an APT attack stage. As expected, there is an overlap between the stages, e.g., a meta-alert from \( Z_0 \) (Internet) to \( Z_1 \) might be an indicator for either Reconnaissance or Delivery. Thus, our goal is not to assign a single APT stage to each alert and meta-alert but rather a set of potential stages. Given the information from Table 1, we obtain four distinct sets of potential APT stages depending on the network direction of alert. Outgoing connections to the Internet (\( Z_0 \)) are labeled with [D2, C, E] and incoming connections with [R, D1]. Internal connections are tagged either with [L, S, O] if both hosts are part of the same zone or [L, S, P, O] if the zones differ between source and destination host.

We have now introduced all fundamentals required for our algorithm. Given the target network topology, we can assign potential APT attack stages to alerts and meta-alerts that we can then connect and combine to construct potential multi-stage attack scenarios based on the NKCSM. Fig. 3 contains all relevant stages of our algorithm. First, we assign potential stages to alerts and meta-alerts obtained from alert correlation. Next, we build an alert graph by linking potential predecessor and successor stages based on the NKCSM to obtain alert graphs. These graphs are then reduced and aggregated to APT infection graphs. Due to the construction this graph can still contain multiple potential multi-stage attack campaigns, so we extract multiple distinct APT scenario graphs. Finally, the set of scenarios is deduplicated and pruned to remove duplicate or trivial scenarios. In the remainder of the section, we explain all of these steps in more detail.

**Example scenario.** Before we continue to the algorithm, we present a small artificial multi-stage attack scenario, that we use as an example throughout the paper to illustrate the process. In this scenario, the target network is divided in two zones \( Z_1 \) and \( Z_2 \) with the following IP subnets:

- \( Z_1 : 10.1.0.0/16 \)
- \( Z_2 : 10.2.0.0/16 \)

The attacker in our scenario aims to find valuable hosts in \( Z_2 \) and uses three attacking machines with public IP addresses (4.4.4.4, 1.3.3.7, 1.4.4.7) throughout the campaign. While a real APT campaign would perform more attack steps, especially after valuable services are discovered, this example is intentionally kept small. The attacker performs the following five steps chronologically:

1. **Reconnaissance:** The attacker uses an Internet host to scan four hosts in \( Z_0 \) (4.4.4.4 \( \rightarrow \) [10.1.0.1, 10.1.0.2, 10.1.0.3, 10.1.0.4]).
2. **Delivery:** The attacker uses another Internet host to deliver a malware-dropper to a host in \( Z_0 \) (1.3.3.7 \( \rightarrow \) 10.1.0.4).
3. **Delivery (Download):** The infected machine downloads a second-stage malware from the Internet (10.1.0.4 \( \rightarrow \) 1.4.4.7).
4. **Pivot:** The malware pivots the infection to two hosts in \( Z_1 \) (10.1.0.4 \( \rightarrow \) [10.2.0.1, 10.2.0.3]).
5. **Discovery:** The malware scans the three remaining machines in \( Z_1 \) for valuable services (10.2.0.3 \( \rightarrow \) [10.2.0.2, 10.2.0.4, 10.2.0.5]).

Alert graph. With the implied transition order from NKCSM and the mapping of alerts to potential APT stages, we can build a directed graph based on pre- and postconditions of each state. Each meta-alert results in a node with the potential stages, sources and targets of the attack attached as additional labels. Two nodes \( u, v \) are connected with an edge \( e \) if three conditions are met:

1. The latest timestamp of \( u \) is smaller than the earliest timestamp of \( v \).
2. The potential APT stages of \( u \) contain at least one stage, that is a precondition for any APT stage of \( v \). If multiple stages match, the ones that compromise new hosts are preferred.
3. The source and target IP addresses of \( u \) and \( v \) match according to the APT stages of \( u \). For stages that move infection (D1, L, P) the target address of \( u \) matches a source address of \( v \). Other APT stages, that do not compromise new hosts, are valid if any source IP address overlaps between \( u \) and \( v \).

The resulting edge \( e \) is then labeled with the set of APT stage preconditions, i.e., the set of APT stages of \( u \) that represent a precondition to any stage of \( v \). Fig. 4 shows such an alert graph that contains six alerts derived from the five stages in our example. For demonstrative purposes we assume that an IDS produced a alert for each malicious action without any false positives.

The alert graph already shows promising results. The path the attackers took throughout the zones is clearly visible. However, we
can already see at least two suboptimal properties of the graph: First, the APT stage labels on the edges are broad and thus sometimes contain more APT stages than only the correct one. This is not a problem, as the more relevant information, i.e., IP addresses and alert identifiers, is contained in the nodes anyway. Second, the alert graph contains edges that do not add any useful information (indicated by dashed lines in the figure) as they lie on a path shorter than the longest path between two nodes. This means, they discard the additional information that is present on the nodes that are not included on these paths. While it is possible, that this represents the actual attack and the skipped node is the result of a false positive alert, the longest path offers more information to the threat hunter (namely the hosts to investigate for further indicators of compromise). Additionally, this type of graph can grow quite large quite easily. Due to the loose requirements for linking two nodes, resulting graphs can be almost fully connected in real-world scenarios. This would not efficiently support human threat-hunters as they cannot extract meaningful information anymore. However, our example graph is relatively compact, it only represents a small attack without any false positives.

**APT infection graph.** We can address the problems of the alert graph by reducing the graph density through elimination of obsolete information and aggregation of existing information. We start the graph consolidation on the node that does not possess any outgoing edges. We can guarantee the existence of at least one such node due to our timestamp requirement on the edges (condition 1 for connecting two nodes in the alert graph). Starting from this node, we recursively iterate through the incoming edges while aggregating those with identical APT stage labels. Longest paths are preferred during the iteration and paths shorter than the longest path between two nodes are discarded. The source and target sets of the connected nodes are combined for matching edges to obtain the set union.

The compact graph obtained by this process is called **APT infection graph**. In this graph, nodes mark APT campaign progress, while the edges represent the APT stages with the related information such as involved IP addresses and alert identifier. Fig. 5 shows the APT infection graph for our example scenario. It is significantly smaller than before, while retaining the important information about IP addresses and stages. The progress of the potential APT campaign is clearly visible, and the reduced branching helps focusing on the important information for threat hunters. The combination of the set of potential APT stages and IP addresses directly hints at how the hosts should be further investigated as the different stages usually leave distinct indicators of compromise on the machine. When we described KCMS and NKCSM, we differentiated between stages that compromise new hosts and stages that do not. Until now we only used this information to prioritize stages while constructing alert graphs. As a result, the APT infection graph might contain edge pairs that represent consecutive stages in the state machine (and thus are valid in the current graph) but have a non-infected host as the source for the second stage. An example for that is given in Fig. 6.

In the figure we see that host 10.0.0.1 gets infected from the Internet ($e_1$). This is followed by some outbound connections from the hosts 10.0.0.1 and 10.0.0.2 ($e_2$) and another outbound connection from 10.0.0.1 only ($e_3$). While the consecutive stages $D1 \rightarrow [D2, E, C] \rightarrow [D2, E, C]$ are valid, the host 10.0.0.2 was never infected on the red path ($e_1, e_2$) and thus cannot be responsible for the outbound connection in $e_3$. If we follow the blue path ($e_4, e_5$) the host is indeed infected, but the source IP for the preceding Delivery stage differs (5.5.5.5). If we consider this transitive validity, the graph actually contains two distinct potential APT scenarios that partially overlap in hosts and the correct solution would be to extract these two scenarios respectively.

**APT scenario graph.** Overall, APT infection graphs provide a decent overview about potential multi-stage attack campaigns. However, as we mentioned, they can still contain edges that can be considered invalid when compared with our original state machine NKCSM. Additionally, they might contain multiple APT scenarios ...
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![Figure 5: APT infection graph for the example scenario without false positives.](image)

![Figure 6: Example for a transitively invalid APT infection graph.](image)

![Figure 7: APT scenario graph representing the APT campaign from the example scenario.](image)

The final set of APT scenario graphs can be further reduced and optimized. Due to the process for graph construction, we can sometimes obtain two graphs, where one is an isomorphic subgraph of the other. In our context, this means, that both graphs describe the same potential APT scenario and the larger graph just contains additional steps that are not present in the smaller one. Similar to the edge elimination step from alert graphs to APT infection graph, we can eliminate these smaller graphs entirely without losing relevant information. While the problem of subgraph isomorphism is known to be NP-complete, it can often be solved efficiently. Our prototype uses the implementation from the Python library networkx that is based on Cordella’s work [4] to prune and deduplicate the final result set. While our prototype does not perform any additional optimization, a real-world deployment can add additional postprocessing of the final set of APT scenario graphs, e.g., prioritization of scenarios that contain a specific critical host or scenarios with the longest chains. As APT and other multi-stage attacks are highly dynamic and tailored to the target, we want to emphasize the opportunities for further optimization here, but leave the actual implementation to the respective target organization.

3.3 Summary

In this section, we described the two core contributions of our paper. We first introduced our formalization of the unified kill chain [19], the kill chain state machine (KCSM) and a reduced variant specific to network-visible stages (network kill chain state machine (NKCSM)). Second, we detailed our graph-based algorithm to produce APT scenario graphs from a set of network alerts and meta-alerts and the topology information of the target network. The scenarios not only represent a significant reduction when compared to the total alert volume, but also offer additional context to human analysts during incident triage and further investigations of potential multi-stage attack present in the network.

4 EVALUATION

We evaluate our algorithm for APT Contextualization in two distinct ways. First, we apply our complete approach, from alert generation to APT contextualization, to the entire unmodified CSE-CIC-IDS2018 [21] dataset. While this dataset does not contain any APT activity by itself, this experiment demonstrates the significant alert volume reduction we can achieve in a realistic scenario. Furthermore, we highlight the real-world applicability of our approach as we process raw network traffic instead of commonly used alert data. Second, we designed an APT attack campaign based on real CVEs, injected PCAPs of the attacks into CSE-CIC-IDS2018 and applied our pipeline again. We explain how the resulting APT Scenario Graphs provide unique insights into the APT campaign and show how the additional context can aid mitigation measures. This
section begins with a brief overview of both the original CSE-CIC-IDS2018 dataset as well as the modified one including our custom APT campaign. Next, we summarize the experimental setup including the different tools and algorithms used for alert generation and correlation. In the last part, we discuss the results obtained on both the unmodified dataset as well the injected APT campaign and show how our approach achieves a significant volume reduction of the alert set and provides additional context about APT campaigns to threat hunters.

### 4.1 Data Sets
To the best of our knowledge, there are no public network traffic data sets containing real APT campaigns. In combination with the highly dynamic nature of APT campaigns this renders the evaluation of detection and correlation approaches difficult. We address this problem by taking a well-known data set for intrusion detection, namely CSE-CIC-IDS2018 [21], and carefully inject a hand-crafted APT campaign into it. To model the individual attack steps of the campaign, we chose known vulnerabilities that were actively exploited. The CSE-CIC-IDS2018 data set is intended for the evaluation of network IDSs and contains seven distinct attacks spanning ten days across six internal network zones/subnets as well as benign traffic. Table 2 shows some key characteristics of the data set. The scope of six internal zones as well as 450 hosts should match a small to mid-sized company well. The duration of our scenarios. We named this campaign IDS2018-APT.

| Property       | Value               |
|----------------|---------------------|
| # Subnets/Zones| 6 + Internet        |
| # Target Hosts | 450                 |
| # Attacker Hosts| 50                  |
| # Connections  | 63 973 325          |
| # (unrelated) attacks | 7              |
| Duration       | 10 days             |
| Size in GB     | 559                 |

Table 2: CSE-CIC-IDS2018: Overview

The APT campaign was injected into the CSE-CIC-IDS2018 data set, which contains benign traffic as well as some unrelated attacks. The PCAP data for the attack steps was collected from various sources across the web: ericconrad.com for *EternalRomance* RCE and trojan download, University of Twente for the *Data Exfiltration Malware* samples and more specifically *Cosmic Duke* C&C traffic and github.com/401trg for PCAPs containing PS-EXEC via SMB. The exfiltration was performed locally, and the traffic recorded via tcpdump. As mentioned before all attacks were chosen on the basis of previous exploitation in the wild, e.g., PS-EXEC is the de facto standard for lateral movement in typical Windows-based enterprise networks at the time of writing. The various PCAP files were then carefully rewritten in both IP addresses and timestamps via tcpdump and editcap to match our APT campaign steps. This process resulted in a coherent attack scenario that took place at the time of the original CSE-CIC-IDS2018 data set (02.18–03.18).

### 4.2 Experimental Setup
Fig. 8 gives an overview across the experimental setup used throughout the evaluation. The scenario PCAPs were processed by *Zeek* as network IDS, resulting in alerts and log files. Next, we used Graph-based Alert Correlation (GAC) [9] as an established alert correlation algorithm. This resembles a real-world deployment with Zeek as the IDS and some alert correlation to reduce alert volume. The processing with GAC yields clustered meta-alerts and unclustered single alerts. Both sets of alerts are persisted in Elasticsearch for later use.

Table 3: IDS2018-APT: Campaign overview

| Day | Attack Source | Target |
|-----|---------------|--------|
| 1   | *EternalRomance* RCE | 1.1.13.37, 172.31.64.67 |
| 1   | 2nd stage trojan download | 172.31.64.67, 12.34.12.34 |
| 4   | *Cosmic Duke* C&C | 172.31.64.67, 1.1.14.47 |
| 8   | PS-EXEC via SMB | 172.31.64.67, 172.31.69.20 |
| 10  | Data exfiltration via HTTPS | 172.31.69.20, 1.1.15.57 |

(1) On day 1 the attackers perform a Remote Code Execution (RCE) via the *EternalRomance* exploit on a vulnerable host in the R&D department of the target organization with the IP address 172.31.64.67.

(2) Directly afterwards, the malware downloads a second stage trojan from a compromised Internet host with the IP address 12.34.12.34 and persists on the machine.

(3) Three days later, the malware performs Command & Control (C&C) communication to the attacker-controlled Internet host 1.1.14.47.

(4) On day 5 the malware moves laterally to a server machine 172.31.69.20 via PS-EXEC, a tool for legitimate Windows remote administration.

(5) On day 10 the compromised server exfiltrates a copy of a core database to the attacker-controlled Internet host 1.1.15.57.

Overall, IDS2018-APT involves four malicious hosts from the Internet (1.1.13.37, 12.34.12.34, 1.1.14.47, 1.1.15.57) and two internal hosts that are targeted by attacks (172.31.64.67, 172.31.69.28). The movement across two zones resembles a potential APT campaign in which the attackers had inside knowledge about the organization’s network segmentation and directly moved to the target server.

The APT campaign was injected into the CSE-CIC-IDS2018 data set, which contains benign traffic as well as some unrelated attacks. The PCAP data for the attack steps was collected from various sources across the web: ericconrad.com for *EternalRomance* RCE and trojan download, University of Twente for the *Data Exfiltration Malware* samples and more specifically *Cosmic Duke* C&C traffic and github.com/401trg for PCAPs containing PS-EXEC via SMB. The exfiltration was performed locally, and the traffic recorded via tcpdump. As mentioned before all attacks were chosen on the basis of previous exploitation in the wild, e.g., PS-EXEC is the de facto standard for lateral movement in typical Windows-based enterprise networks at the time of writing. The various PCAP files were then carefully rewritten in both IP addresses and timestamps via tcpdump and editcap to match our APT campaign steps. This process resulted in a coherent attack scenario that took place at the time of the original CSE-CIC-IDS2018 data set (02.18–03.18).

1https://www.ericconrad.com/2017/04/shadowbrokers-pcaps-etc.html
2https://www.utwente.nl/en/eemcs/scs/downloads/20171127_DEM/
3https://github.com/401trg/detections/tree/master/pcaps
in the APT contextualization. Our prototype implementation of the APT contextualization is written in Python and leverages the `networkx` library for graph processing.

For alert generation we use Zeek v3.1.4 in two distinct configurations that we call MIN and FULL. MIN loads almost all scripts that Zeek provides per default. Notable exceptions include file extraction, as the transferred files are not needed in the process, and SSL/TLS/OCSP verification, as these scripts produce false positives for the self-signed certificates that are used in CSE-CIC-IDS2018. In addition to the default scripts, we wrote some Zeek scripts tailored to our organization scenario including detection of downloaded Windows executables and large outgoing network communication. These organization-specific scripts are not written to exactly detect the attack steps of our APT campaign directly, but rather match the overall scenario of a mostly Windows-based enterprise network. As a result, they produce false positives especially as the traffic unrelated to our APT campaign also consists of the same protocols that the scripts monitor, e.g., SMB. MIN therefore resembles an organization that customizes Zeek to some extent, however, does not include any third-party scripts for improved visibility. The FULL configuration loads all scripts from MIN and adds two well-known third-party scripts, namely `mitre-attack/bzar`\(^4\) for the detection of adversarial activity related to Mitre’s ATT&CK framework and `0x13x1/zeek-EternalSafety`\(^5\) for detecting potentially malicious SMBv1 protocol violations that are used in the Eternal family of Windows exploits. FULL therefore resembles a realistic setup in high-security environments, in which security administrators perform proactive threat hunting to detect APT campaigns. The MITRE ATT&CK framework is well known in the community and aimed at detecting attack steps of multi-step attacks such as APT campaigns. Both configurations are examples for organizations with different threat profiles. MIN includes less scripts and might therefore miss important attack steps. FULL includes scripts that will result in an increased alert volume with more false positives, which will also complicate successful detection of APT campaigns. We include both configurations to show the range of scenarios our approach addresses.

GAC [9] was chosen as state-of-the-art approach for alert correlation. This step is essential to reduce the alert volume. GAC achieves this via clustering, however any correlation algorithm can be used as both meta-alerts and single alerts are ingested for the APT contextualization. GAC was run on batches of all alerts once per day in the data set to simulate a realistic scenario where

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\(^4\)https://github.com/mitre-attack/bzar

\(^5\)https://github.com/0x13x1/zeek-EternalSafety

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**Figure 8: Full experimental setup for End-to-End APT Contextualization.**

| Level | Metric | MIN | FULL |
|-------|--------|-----|------|
| Zeek  | Alerts | 12735 | 446458 |
| GAC   | Alerts for Contextualization | 4510 | 50478 |
| APT   | APT infection graphs | 511 | 491 |
|       | Total APT scenario graphs | 4418 | 4253 |
|       | Distinct APT scenario graphs | 642 | 700 |
|       | Volume reduction | 5.04% | 0.16% |

**Table 4: IDS2018: Results Overview**

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batch-based alert correlation algorithms are run in fixed intervals. We also experimented with DECANTeR [3] to reveal C&C communication and produce stage-alerts accordingly. However, in our experiments, DECANTeR was unable to correctly identify the C&C communication in our APT campaign and was thus not included in the final evaluation. Nonetheless, our approach is not strongly tied to any alert correlation or APT stage detection scheme. Other alert correlation approaches can be used and stage-specific alerts for any APT stage are supported.

### 4.3 Results

**Volume reduction on unmodified data set.** In the first experiment, we evaluate the real-world feasibility of our approach by processing the unmodified CSE-CIC-IDS2018 data set [21]. As the data set does not contain an APT campaign, all results can be considered false positives. However, the results and especially the number of `APT scenario graphs` should help to estimate the amount of manual analysis work that is required to be performed by security personnel when using our approach in day-to-day work. Thus, the experiment will establish a baseline to compare the following experiment with the injected IDS2018-APT scenario. As mentioned before, CSE-CIC-IDS2018 does contain both external and internal attacks unrelated to the APT campaign, e.g., brute-forcing, an infiltration attack originating from an internal host or DDoS originating from a botnet. This should be representative of real-world networks that may be targeted by outside attacks as well as some internal noise.

Table 5 contains the results for both Zeek configurations for the unmodified data set. The MIN configuration produced 12735 Zeek alerts that GAC further clustered to 125 meta-alerts and 4385 unclustered alerts. Thus 4510 total alerts were used as input for the APT contextualization. This resulted in 511 APT infection graphs which were split into 4418 total APT scenario graphs that were deduplicated and pruned to 642 graphs. Over the experiment duration of ten days, this amounts to approximately 34.2 potential APT scenarios per day that need to be manually analyzed by human analysts. While this number initially may seem high, it is not unreasonable to assume that a security operation center (SOC) of an organization with 450 networked hosts would be able to accomplish. This is especially likely as the alternative would be to manually investigate all 12735 alerts in isolation and without additional context offered by our APT scenario graphs. Overall our approach yields a significant volume reduction to 5.04% of the original alert set. The
results for the FULL configuration are similar and partially even better. In total Zeek produced 446,458 alerts. This significant increase, when compared to the MIN configuration, is the result of adding including scripts with higher volume output. By applying GAC, we obtained 10,724 meta-alerts and 39,754 unclustered alerts. The APT contextualization of these 50,478 total meta-alerts yields 491 APT infection graphs and 4,253 total APT scenario graphs, respectively. For the FULL configuration, the deduplication and pruning proved to be highly effective. It reduced the number of potential scenarios from 4,253 to 700. When compared to our original alert set of 446,458 alerts, this number resembles an even larger volume reduction to 0.16%. This shows the potential of our approach especially for larger alert sets.

The results from this experiment indicate that our approach for APT contextualization is able to achieve a significant reduction in alert volume up to 0.16% of the original alert set. While the absolute numbers of APT scenario graphs per day, that are false positives in this case, is not negligible with 34.2 and 70 it is not unreasonable to assume that a SOC would be able to handle these numbers via analysts especially in high-security contexts. Additionally, it is important to note that our contextualization so far is based on network data only. Additional IoCs, e.g., obtained from host IDSs or sensors, can be leveraged to further filter the set of APT scenario graphs and to offer additional context to prioritize graphs for manual analysis.

**APT campaign detection & characterization.** In the second experiment, we evaluate the detection performance of our approach on the synthetic APT campaign described above, that we called IDS2018-APT. Table 5 summarizes results of the contextualization process for both Zeek configurations. The final numbers of APT scenario graphs with 611 (MIN) and 686 (FULL) respectively result in volume reductions similar to the unmodified data set. To evaluate the functional correctness of our contextualization approach, we evaluate the groundtruth starting from the alert level up to the generated APT scenario graphs.

**Zeek alerts.** Table 6 shows all alerts generated by Zeek for the two different configurations grouped by their alert type. The first block contains alerts generated by scripts that were shipped with Zeek. The second block contains all scripts written by us tailored to the organization scenario (prefixed with "Org"). The third and fourth blocks are only included in the FULL configuration and contain alerts produced by Mitre’s BZAR (prefixed with "ATTACK") and EternalSafety (prefixed with that name) respectively. For each alert type and configuration, the table lists the total number of alerts observed of that type, the total number of alerts that were produced as a result of our injected APT campaign, and the ratio between all alerts of that type and the ones related to the campaign. This ratio is the true positive rate (TPR) related to our APT campaign. The remaining alerts are the result of either attacks unrelated to the APT (as present in the original data set) or false positives. The table shows that the overall ratio of alerts related to the APT campaign is very small with 0.0237% for MIN and 0.000245% for FULL, respectively. The type of alerts provides some insight about which parts of our APT campaign were detected. The organization-specific script related to executables over a non-HTTP channel revealed the second stage trojan download on day 1, while the SMB script detected the PS-EXEC lateral movement on day 8. The alert Org::Very_large_Outgoing_Tx was generated for the exfiltration on the last day. Overall four out of the 12,675 total alerts produced by the MIN configuration relate to IDS2018-APT in some way. In the FULL configuration, BZAR adds seven additional APT related alerts that are all caused by the lateral movement. EternalSafety produces three more APT related alerts as a result of the initial EternalRomance remote code execution (RCE) on day 1. While the alerts EternalSafety::DoublePulsar and EternalSafety::EternalSynergy are all related to our APT campaign, the other types and EternalSafety::ViolationTx2Cmd produce high volumes of unrelated alerts and are responsible for a large increase of alerts from MIN to FULL.

Summing up, the MIN configuration produced Zeek alerts for the second stage trojan download, the lateral movement via PS-EXEC, and the data exfiltration. It missed the initial RCE and the Cosmic Duke C&C communication, which thus cannot be contained in any further processing. The FULL configuration improves the detection of lateral movement via additional alerts from BZAR, while the EternalSynergy packages is able to produce a few alerts related to the initial RCE among a large number of false positives.

**Meta-alerts and single alerts.** After correlation via GAC, we obtained clustered meta-alerts and unclustered singleton that both serve as input for the APT contextualization. Table 7 shows which meta-alerts and singleton alerts are related to IDS2018-APT for both configurations. For the MIN configuration GAC produced 119 meta-alerts and 4,432 unclustered alerts. Out of these total 4,551 alerts, only three singleton alerts are related to IDS2018-APT. This reinforces the expectation, that alerts caused by APT activity are not clustered by traditional alert correlation algorithms. Given these results we expect an accurate contextualization result as all alerts contain single IP addresses for as source and destination. In the FULL configuration GAC generated 10,713 meta-alerts and 39,649 singleton alerts. Compared to the unmodified data set these numbers are in the expected range. Out of the four relevant alerts, we see three singleton alerts for the same attack steps as in MIN plus an additional alert for the initial RCE as expected from the Zeek alerts show previously. However, the alert that captured this step is a meta-alert clustered by GAC and contains multiple source IP addresses. This has two implications: First, the resulting APT scenario graph will likely contain all eight IP addresses as the algorithm cannot split this set without additional intelligence. Second, this

| Table 5: IDS2018-APT: Result Overview |
|--------------------------------------|
| Level  | Metric            | MIN | FULL  |
|--------|-------------------|-----|-------|
| Zeek   | Alerts            | 12,675 | 446,407 |
| GAC    | Meta-Alerts       | 119 | 10,713 |
|        | Singleton Alerts  | 4,432 | 39,649 |
|        | Alerts for Contextualization | 4,551 | 50,362 |
| APT    | APT Infection graphs | 442 | 456 |
|        | Total APT Scenario graphs | 3,452 | 4,305 |
|        | Distinct APT Scenario graphs | 611 | 686 |
|        | Volume Reduction  | 4.82% | 0.15% |
Table 6: IDS2018-APT: Groundtruth in Zeek Alerts

| Source Alert Type                     | IDS2018-APT-MIN |        |        | IDS2018-APT-FULL |        |        |
|---------------------------------------|-----------------|--------|--------|-----------------|--------|--------|
| Conn::Retransmission_Inconsistency    | 1 171           | 0      | 0.00   | 1 171           | 0      | 0.00   |
| SSL::Weak_Key                         | 120             | 0      | 0.00   | 120             | 0      | 0.00   |
| Org::Stalled_HTTP_Connection          | 4 976           | 0      | 0.00   | 4 976           | 0      | 0.00   |
| Org::HTTP_Executable_Dl               | 6               | 0      | 0.00   | 6               | 0      | 0.00   |
| Org::NON_HTTP_Executable_Dl           | 4               | 1      | 0.25   | 4               | 1      | 0.25   |
| Org::SM_Executable_File_Transfer      | 1               | 1      | 1.00   | 1               | 1      | 1.00   |
| Org::Javascript_Web_Injection_URI      | 336             | 0      | 0.00   | 336             | 0      | 0.00   |
| Org::SQL_Web_Injection_URI            | 78              | 0      | 0.00   | 78              | 0      | 0.00   |
| Org::Web_Login_Guessing               | 14              | 0      | 0.00   | 14              | 0      | 0.00   |
| Org::Large_Outgoing_Tx                | 5 772           | 0      | 0.00   | 5 772           | 0      | 0.00   |
| Org::Multiple_Large_Outgoing_Tx       | 187             | 0      | 0.00   | 187             | 0      | 0.00   |
| Org::Very_Large_Outgoing_Tx           | 10              | 1      | 0.10   | 10              | 1      | 0.10   |
| ATTACK::Execution                     |                |        |        | 2               | 2      | 1.00   |
| ATTACK::Lateral_Movement              |                |        |        | 4               | 4      | 1.00   |
| ATTACK::Lateral_Movement_Extracted_File |            |        |        | 1               | 1      | 1.00   |
| EternalSafety::DoublePulsar           |                |        |        | 1               | 1      | 1.00   |
| EternalSafety::EternalBlue            |                |        |        | 53              | 0      | 0.00   |
| EternalSafety::EternalSynergy         |                |        |        | 1               | 1      | 1.00   |
| EternalSafety::ViolationCmd           |                |        |        | 1 389           | 0      | 0.00   |
| EternalSafety::ViolationNtRename      |                |        |        | 8 731           | 0      | 0.00   |
| EternalSafety::ViolationPidMid        |                |        |        | 6 133           | 0      | 0.00   |
| EternalSafety::ViolationTx2Cmd        |                |        |        | 408 686         | 1      | 0.000002 |
| Signatures::Sensitive_Signature       |                |        |        | 8 731           | 0      | 0.00   |
| Total                                 | 12 675          | 3      | 0.000237 | 446 407         | 13     | 0.00000245 |

Table 7: IDS2018-APT: Groundtruth after clustering via GAC [9]

| Attack Step                          | IDS2018-APT-MIN |        |        | IDS2018-APT-FULL |        |        |
|--------------------------------------|-----------------|--------|--------|-----------------|--------|--------|
| EternalRomance RCE                   |                |        |        | Meta 1.1.13.37   | 1.1.13.37 | 172.31.64.67 |
| 2nd stage trojan download            | Single 172.31.64.67 | 12.34.12.34 | Single 172.31.64.67 | 12.34.12.34 |
| Cosmic Duke C&C                      | --              |        |        | --              | --            |
| PS-EXEC via SMB                      | Single 172.31.64.67 | 172.31.69.20 | Single 172.31.64.67 | 172.31.69.20 |
| Data exfiltration via HTTPS          | Single 172.31.69.20 | 1.1.15.57 | Single 172.31.69.20 | 1.1.15.57 |

Example shows that meta-alerts may also carry (partial) information related to APTs. While the results from the MIN configuration may indicate that it is sufficient to only investigate unclustered singleton alerts, this does not hold in the FULL configuration. In summary, we expect a similar contextualization result compared to MIN with more details about the initial point of infection.

APT scenario graphs. For the MIN configuration, the APT Contextualization yielded 611 distinct APT scenario graphs. From the original set of 12 675 alerts, this implies a reduction to 4.82%. Among the result set is one graph that describes our APT campaign. Fig. 9a shows the APT scenario graph that was generated from the alerts of IDS2018-APT. As mentioned before the initial infection via EternalRomance and the Cosmic Duke C&C did not generate an alert and are thus not included in the graph. Most stages are labeled correctly with IP addresses and APT stages. The only imprecision relates to the second stage trojan download, as the edge is labeled ambiguously with [E, D2, C] and the corresponding node not only contains the target IP address 12.34.12.34 but the label 'Internet'. The stage mismatch is expected as our approach derives potential stages from network direction and can not reduce the set of stages further without additional context for outgoing connections to the Internet. The label is the result of imperfect meta-alert generation as the algorithm grouped multiple Internet IP addresses and thus produced that label. However, the scenario references all used meta-alerts and single alerts via a unique identifier. The MAX configuration produced an alert for the initial RCE that was...
missed in MIN. Ideally, the produced APT scenario graph should thus correctly identify the first node in the chain that is labeled as with \(<\text{empty}>\) in Fig. 9a. The contextualization yielded 686 distinct APT scenario graphs—a reduction to 0.15% of the total alert set. Fig. 9b shows the one that closely resembles our APT campaign.

The APT scenario graph matches our campaign with similar precision than the first. The initial RCE is picked up and added to the scenario. However, as there were multiple alerts related to incoming connections to 172.31.64.67, the node is labeled with “Internet”. The referenced alerts indeed contain the one related to the RCE. Overall the FULL scenario matches the campaign more closely as expected from the generated alerts. A human analyst could now use this graph to further investigate the referenced alerts and underlying connections to reveal the APT campaign.

In summary our evaluations indicate that our approach works as intended. First, it significantly reduces the overall set of alerts to be investigated by two to three orders of magnitude and second, it can detect and contextualize complex attacks. Although not all nodes are labeled perfectly, large parts of our APT campaign are visualized. While our APT campaign is obviously not representative of all potential APT campaigns it does include zone movement that is characteristic of typical multi-stage attacks. The movement of the attacker across hosts in different zones should result in longer paths. The movement of the attacker across hosts in different zones should result in longer paths.

5 CONCLUSION

Security operations teams must make sense of huge amounts of log and alert data to find attacks before they become major breaches. But the high volume and false positive rate can quickly cause alert fatigue, resulting in important attacker signals drowning in the noise. In this paper we present a method to substantially reduce the alert volume using alert correlation and attack contextualization. Instead of sifting through hundreds of thousands singleton alerts, analysts can now triage incidents using multi-stage scenario graphs produced by our algorithm. We achieve this by building a kill chain state machine (KCSM) that operates on clustered alert data to identify states and transitions of multi-stage attacks. The resulting APT scenario graphs visualize potential APT campaigns in the network and provide actionable context during investigations. Our algorithm uses correlated meta-alerts as well as unclustered single alerts to construct APT scenario graphs that offer context about potential multi-stage attacks in the network to human analysts.

We evaluated our contextualization approach on the CSE-CIC-IDS2018 data set [21] to quantify the operational overhead for real-world scenarios in two different IDS configurations. For the minimal configuration our approach generated 642 from 12 735 alerts in the ten-day period, a reduction to 5.04%. In the high-security configuration, the algorithm reduced 446 458 alerts to 700, achieving a reduction to 0.16%. This two to three orders of magnitude reduction brings the data into a range that is feasible for human analysts to process. Furthermore, we designed a custom APT campaign on pcap level comprised of exploits that have been actively used in complex attacks and evaluated the contextualization performance of our approach. For both IDS configurations, our approach is able to achieve a comparable reduction as in the unmodified data set while adding additional context about infected IP hosts and potential stages between them. This information helps threat hunters to prioritize hosts in further investigations. In both configurations, the algorithm produced a graph that contains all parts of our scenario that were detectable, i.e., an alerts was present at the lowest level. Our approach is largely based on network direction and derives potential APT stages from the movement between network zones. As attackers generally need to traverse multiple network zones in any enterprise network to reach their targets, we are confident, that the algorithm is able to track large parts of such campaigns as long as any alerts are generated. The stage deduction based on network direction makes the approach very flexible as it does not require special information in the underlying alerts and thus can be applied to any network based alert. Furthermore, our algorithm can also process additional stage-specific alerts and incorporate the resulting attack stages into the APT scenario graphs.

While our results are already quite promising, the number of potential scenarios can be further improved. Our algorithm currently only processes network-level information. In the future, we plan to integrate host-level as well as user identity context for richer scenario graphs and more opportunities to eliminate false positives.
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