Enabling Efficient Cyber Threat Hunting With Cyber Threat Intelligence

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Abstract—Log-based cyber threat hunting has emerged as an important solution to counter sophisticated cyber attacks. However, existing approaches require non-trivial efforts of manual query construction and have overlooked the rich external knowledge about threat behaviors provided by open-source Cyber Threat Intelligence (OSCTI). To bridge the gap, we propose Efficient Hunter, a system that facilitates cyber threat hunting in computer systems using OSCTI. Built upon mature system auditing frameworks, Efficient Hunter provides (1) an unsupervised, light-weight, and accurate NLP pipeline that extracts structured threat behaviors from unstructured OSCTI text, (2) a concise and expressive domain-specific query language, TBQL, to hunt for malicious system activities, (3) a query synthesis mechanism that automatically synthesizes a TBQL query for threat hunting from the extracted threat behaviors, and (4) an efficient query execution engine to search the big audit logging data. Evaluations on a broad set of attack cases demonstrate the accuracy and efficiency of Efficient Hunter in enabling practical threat hunting.

I. INTRODUCTION

Recent cyber attacks have plagued many well-protected businesses [1–3]. These attacks often exploit multiple types of vulnerabilities to infiltrate into target systems in multiple stages, posing challenges for effective countermeasures. To counter these attacks, ubiquitous system auditing has emerged as an important approach for monitoring system activities [4–9]. System auditing collects system-level auditing events about system calls from OS kernel as system audit logs. The collected system audit logging data further enables approaches to hunt for cyber threats via query processing [10–13].

Cyber threat hunting in enterprises is the process of proactively and iteratively searching for malicious actors and indicators in various types of logs, which is critical to early-stage detection and timely system recovery. Despite numerous research outcomes [10–13] and industry solutions [14, 15], existing approaches, however, require non-trivial efforts of manual query construction and have overlooked the rich external knowledge about threat behaviors provided by open-source Cyber Threat Intelligence (OSCTI). Hence, the current threat hunting process is labor-intensive and error-prone.

OSCTI is a form of evidence-based knowledge and has received growing attention from the community, enabling companies and organizations to gain visibility into the fast-evolving threat landscape [16]. Commonly, knowledge about threats is presented in a vast number of publicly available OSCTI sources. Structured OSCTI feeds [17–21] have primarily focused on Indicators of Compromise (IOCs), such as malicious file/process names, IP addresses, and domain names. Though useful in capturing fragmented views of threats, these disconnected IOCs lack the capability to uncover the complete threat scenario as to how the threat unfolds into multiple steps. Consequently, defensive solutions that rely on these low-level, fragmented indicators [14, 15] can be easily evaded when the attacker re-purposes the tools and changes their signatures. In contrast, unstructured OSCTI reports [22, 23] contain more comprehensive knowledge about threats. For example, descriptive relationships between IOCs contain knowledge about multi-step threat behaviors (e.g., “read” relationship between two IOCs “/bin/tar” and “/etc/passwd” in Figure 2), which is critical to uncovering the complete threat scenario. Besides, such connected threat behaviors are tied to the attacker’s goals and thus more difficult to change. Unfortunately, prior approaches do not provide an automated way to harvest such knowledge and use it for threat hunting.

Challenges. In this work, we seek to design automated techniques to (1) extract knowledge about threat behaviors (IOCs and their relationships) from unstructured OSCTI reports, and (2) use the extracted knowledge to enable efficient threat hunting. We identify two major challenges. First, accurately extracting threat knowledge from natural-language OSCTI text is not trivial. This is due to the presence of massive nuances particular to the security context, such as special characters (e.g., dots, underscores) in IOCs. These nuances confuse most NLP modules (e.g., sentence segmentation, tokenization), making existing information extraction tools ineffective [24–26]. Second, system auditing often produces a huge amount of daily logs (0.5 GB ~ 1 GB for 1 enterprise host [10, 11, 27]), and hence threat hunting is a procedure of “finding a needle in a haystack”. Such a big amount of log data poses challenges for solutions to store and query the data efficiently to hunt for malicious behaviors in systems. Besides, to meet the requirement of timely threat hunting, knowledge extraction from OSCTI text also needs to be efficient.

Contribution. We propose Efficient Hunter, a system that facilitates threat hunting in computer systems using OSCTI. We built Efficient Hunter (~ 25K LOC) upon mature system auditing frameworks [28–30] for system audit logging data collection.
structured threat behavior representation is more amenable to IOC relations. Compared to the unstructured OSCTI text, such graph threat behavior and efficient threat behavior extraction. The extracted threat parsing-based IOC relation extraction) to achieve accurate collection of techniques (e.g., IOC protection, dependency requirement of timely threat hunting, the pipeline adopts a been studied in prior work. To handle nuances and meet the requirement of timely threat hunting, the pipeline adopts a collection of techniques (e.g., IOC protection, dependency parsing-based IOC relation extraction) to achieve accurate and efficient threat behavior extraction. The extracted threat behaviors are represented in a structured threat behavior graph, in which nodes represent IOCs and edges represent IOC relations. Compared to the unstructured OSCTI text, such structured threat behavior representation is more amenable to automated processing and integration (Section III-C).

(1) Unsupervised, Light-Weight, and Accurate NLP Pipeline for Threat Behavior Extraction: EffHUNTER employs a specialized NLP pipeline that targets the unique problem of IOC and IOC relation extraction from OSCTI text, which has not been studied in prior work. To handle nuances and meet the requirement of timely threat hunting, the pipeline adopts a collection of techniques (e.g., IOC protection, dependency parsing-based IOC relation extraction) to achieve accurate and efficient threat behavior extraction. The extracted threat behaviors are represented in a structured threat behavior graph, in which nodes represent IOCs and edges represent IOC relations. Compared to the unstructured OSCTI text, such structured threat behavior representation is more amenable to automated processing and integration (Section III-C).

(2) Domain-Specific Query Language & Query Synthesis: To facilitate threat hunting over system audit logging data, EffHUNTER has an efficient query subsystem that employs a concise and expressive domain-specific query language, Threat Behavior Query Language (TBQL), to query the audit logging data stored in different database backends. TBQL is a declarative query language that uniquely integrates a series of critical primitives for threat hunting in computer systems. For example, TBQL treats system entities (i.e., files, processes, network connections) and system events (i.e., file events, process events, network events) as first-class citizens, and provides explicit constructs for entity/event types, event operations, event path patterns, and various types of filters. With TBQL, complex multi-step system behaviors can be easily specified and searched for (Section III-D).

Furthermore, to bridge the threat behavior graph with the query sub-system, EffHUNTER employs a query synthesis mechanism to automatically synthesize a TBQL query from the graph. This way, the external knowledge about threat behaviors can be automatically converted to the TBQL query patterns of system behaviors and integrated in threat hunting. No prior work has proposed a query language for threat hunting that supports the same set of features as supported in TBQL, and has considered the automation of the threat hunting procedure via query synthesis (Section III-E).

It is important to note that EffHUNTER also supports human-in-the-loop analysis via query editing: security analysts can further revise the synthesized query to encode domain knowledge about the specific enterprise environment. In practice, threat hunting is an iterative process that involves multiple rounds of query editing and execution, and the conciseness and declarative nature of TBQL make this process efficient.

(3) Efficient Query Execution: To query the big data efficiently, EffHUNTER employs specialized optimizations for data storage and query execution engine. In particular, EffHUNTER employs data reduction techniques to merge excessive system events while preserving adequate information for threat hunting. To execute a TBQL query, EffHUNTER breaks it into different parts and compiles each part into a semantically equivalent SQL or Cypher data query. EffHUNTER then employs a scheduling algorithm to schedule the execution of these data queries in different database backends, based on their estimated pruning power and semantic dependencies. Compared to the naive plan that compiles the TBQL query into a giant SQL or Cypher query to execute, our execution plan avoids the weaving of many joins and constraints together (which often leads to slow performance) and leverages the query semantics to speed up the execution (Section III-F).

Evaluation. We deployed EffHUNTER on a physical testbed and performed a broad set of attack cases to evaluate various aspects of the system. The evaluation results demonstrate that: (1) EffHUNTER is able to accurately extract threat behaviors from OSCTI text (96.64% F1 for IOC extraction, 92.59% F1 for IOC relation extraction), performing much better than general information extraction approaches (< 5% F1); (2) EffHUNTER is able to accurately find malicious system activities using OSCTI text (98.34% F1); (3) the entire pipeline of EffHUNTER is efficient. The threat behavior extraction and query synthesis parts take 0.52s on average. For query execution, TBQL queries execute 22.7x faster than SQL queries for PostgreSQL backend, and 9.1x faster than Cypher queries for Neo4j backend; (4) TBQL queries are more concise than SQL queries (> 2.8x) and Cypher queries (> 2.2x).

To the best of our knowledge, EffHUNTER is the first system that bridges OSCTI with system auditing to enable efficient cyber threat hunting in computer systems. Additional evaluation details and a system demo video are available on our project website [33].
II. SYSTEM OVERVIEW

Figure 1 shows the architecture of EffHunter. At a high level, EffHunter has two subsystems: (1) a threat behavior extraction pipeline for automated threat knowledge extraction, and (2) a query subsystem built upon system auditing, which provides a domain-specific query language, TBQL, to hunt for threats in computer systems. In the query subsystem, monitoring agents built upon mature system auditing frameworks [28]–[30] are deployed across hosts to collect system audit logging data. The collected data is then sent to the central database for storage. Given an input OSCTI report, EffHunter first extracts IOCs (e.g., file names, file paths, IPs) and their relations, and constructs a threat behavior graph. EffHunter then synthesizes a TBQL query from the threat behavior graph, and executes the query to find the matched system auditing records. Security analysts can optionally revise the synthesized query to encode expert domain knowledge. In the situation where the OSCTI report is not available or contains little useful information, security analysts can use EffHunter as a proactive threat hunting tool and manually construct TBQL queries for execution.

Demo Example. Figure 2 shows an example data leakage attack case to demonstrate the whole processing pipeline. The case was constructed based on the Cyber Kill Chain framework [34] and CVE [35], and used in our evaluation (i.e., Case nu_2). As we can see, the threat behavior graph clearly shows how the threat unfolds into multiple connected steps, where each step is represented by an IOC node-edge triplet. Furthermore, each edge is associated with a sequence number indicating the order of the threat step. Such sequential information is essential to uncovering the correct threat scenario and has not been considered in prior work [24]–[26]. The synthesized TBQL query further encodes the threat knowledge into formal query constructs, which is more amenable to human-in-the-loop analysis and iterative exploration. Nodes and edges in the threat behavior graph are synthesized into system entities and system event patterns in the TBQL query, and the sequence numbers of edges are used to construct a with clause that specifies the temporal order constraints of system event patterns. By default, the synthesized TBQL query specifies the default attributes of all system entities (i.e., “name” for files, “exename” for processes, and “dstep” for network connections) in the return clause.

Threat Model. Our threat model follows the prior work on system auditing [4]–[11]. We assume an attacker that attacks the computer system from outside: the attacker either utilizes

the vulnerabilities in the system or convinces the user to download files with malicious payload. We also assume that OS kernels and kernel-layer auditing frameworks [28]–[30] are part of our trusted computing base, and the system audit logging data collected from kernel space is not tampered. Any kernel-level attacks that deliberately compromise system auditing frameworks are beyond the scope of this work. We also do not consider the attacks that do not go through kernel-layer auditing (e.g., side channel attacks, memory-based attacks) and thus cannot be captured by the system auditing frameworks. Kernel hardening techniques and finer-grained auditing tools [50] could be integrated to address these types of attacks, which are beyond the scope of this work.

III. DESIGN OF EFFHUNTER

A. System Auditing

EffHunter leverages mature system auditing frameworks [28]–[30] to collect system-level audit logs about system calls from the OS kernel. The collected kernel audit logs consist of system events that describe the interactions among system entities, which are crucial for security analysis. As shown in previous studies [4]–[11], on mainstream operating systems, system entities in most cases are files, processes, and network connections, and the monitored system calls are mapped to three major types of system events: file access, processes creation and destruction, and network access. Hence, in EffHunter, we consider system entities as files, processes, and network connections. We consider a system event as the interaction between two system entities represented as (subject_entity, operation, object_entity), which consists of the initiator of the interaction, the type of the interaction, and the target of the interaction. Subjects are processes originating from software applications (e.g., Chrome), and objects can
be files, processes, and network connections. We categorize system events into three types according to the types of their object entities: file events, process events, and network events.

EffHUNTER parses the collected audit logs into a sequence of system events among system entities, and extracts a set of attributes that are crucial for security analysis. Table I shows the representative system calls (in Linux) processed by EffHUNTER. Tables II and III show the representative attributes of entities and events extracted by EffHUNTER.

To uniquely identify system entities, for a process entity, EffHUNTER uses the process executable name and PID as its unique identifier. For a file entity, EffHUNTER uses the absolute path as its unique identifier. For a network connection entity, as processes usually communicate with servers using different network connections but with the same IPs and ports, treating these connections differently greatly increases the amount of data we trace and such granularity is not required in most cases [9], [10]. Thus, EffHUNTER uses 5-tuple (srcip, srcport, dstip, dstport, protocol) as a network connection’s unique identifier. Failing to distinguish different entities will cause problems in relating events to entities.

B. Data Storage

EffHUNTER stores the parsed system entities and system events in databases, so that the system audit logging data can be persisted. Prior work has modeled system audit logging data as either relational tables [10] or provenance graphs [9]. Inspired by such designs, EffHUNTER adopts two types of database models for its storage component: relational model and graph model. Relational databases come with mature indexing mechanisms and are scalable to massive data, which are suitable for queries that involve many joins and constraints. Graph databases represent data as nodes and edges, which are suitable for queries that involve graph pattern search.

In the current design, EffHUNTER adopts PostgreSQL [31] for its relational data storage and Neo4j [32] for its graph data storage. For PostgreSQL, EffHUNTER stores system entities and system events in separate tables. For Neo4j, EffHUNTER stores system entities as nodes and system events as edges. Indexes are created on key attributes (e.g., file name, process executable name, source IP, destination IP) for both databases to speed up the search. In Section III-E and III-F we will describe in detail how EffHUNTER executes different types of TBQL queries in different database backends seamlessly.

Algorithm 1: Threat Behavior Extraction Pipeline

| Input | OSCTI Text: document |
| Output | Threat Behavior Graph: graph |
| 1 | Initialize all_block_trees; |
| 2 | Initialize all_ioc_relations; |
| for block in SegmentBlock (document) do |
| Initialize trees; |
| block, replacementRecord ← ProtectLoc (block); |
| for sentence in SegmentSentence (block) do |
| tree ← ParseDependency (sentence); |
| Align replacementRecord with tree; |
| tree ← RemoveLocProtection (tree, replacementRecord); |
| tree ← AnnotateTree (tree); |
| tree ← SimplifyTree (tree); |
| Add tree to trees; |
| for tree in trees do |
| tree ← ResolveCoref (tree, trees); |
| Add all tree in trees to all_block_trees; |
| all_iocs ← ScanMergeIoc (all_block_trees); |
| for tree in trees do |
| ioc_relations ← ExtractIocRelation (tree, trees, all_iocs); |
| Add ioc_relations to all_ioc_relations; |
| graph ← ConstructGraph (all_iocs, all_ioc_relations); |

are objects; suppose e1 occurs before e2 will be merged if: u1 = u2 && v1 = v2 && e1.operationType = e2.operationType && 0 ≤ e2.startTime − e1.endTime ≤ threshold; (2) the attributes of the merged event are updated as: em.startTime = e1.startTime, em.endTime = e2.endTime, em.dataAmount = e1.dataAmount + e2.dataAmount. The merge process is done iteratively on all edges between the paired entities until none can be further merged. We experimented with different threshold values and chose 1 second, as it has reasonable reduction performance in merging system events for file manipulations, file transfers, and network communications, with no false events generated.

C. Threat Behavior Extraction

As mentioned in Section I, massive nuances exist in OSCTI text (e.g., dots, underscores in IOCs), which limit the performance of most NLP modules and existing information extraction tools [24]–[26]. To address the unique challenge, EffHUNTER employs a specialized NLP pipeline to handle nuances and accurately extract IOCs and their relations to construct a threat behavior graph. Furthermore, our pipeline is unsupervised and light-weight. Algorithm 1 gives the pipeline:

Step 1: Block Segmentation (Line 3): Most of the OSCTI articles have natural block structure, and different blocks of an article might talk about different threat behaviors. To improve both accuracy and efficiency, we segment an article into blocks, and extract IOCs and their relations from each block.
block. Later on, when we construct the threat behavior graph, we will link the same IOCs that appear across multiple blocks.

**Step 2: IOC Recognition and IOC Protection (Line 5):** We construct a set of regex rules by extending an open-source IOC parser [37] (we made improvements to improve its coverage, e.g., distinguishing Linux/Windows file paths) to recognize different types of IOCs (e.g., file name, file path, IP). Furthermore, we protect the security context by replacing the IOCs with a dummy word (we use the word “something”) and leave a replacement record. This makes the NLP modules designed for processing general text work well for OSCTI text.

**Step 3: Sentence Segmentation (Line 6):** After protecting the security context, we leverage a general-purpose sentence segmentation component [38] to segment a block into sentences.

**Step 4: Dependency Parsing (Line 7):** After sentence segmentation, we construct a dependency tree for each sentence by using a dependency parsing component that was pretrained on a large general corpus (i.e., English multi-task CNN trained on OntoNotes in spaCy [38]). We then use the replacement record of IOCs to restore the security context by replacing the dummy word with the original IOCs.

**Step 5: Tree Annotation (Line 10):** Among all nodes in the dependency trees, there are some nodes whose associated tokens are particularly useful for coreference resolution and relation extraction (e.g., IOCs, candidate IOC relation verbs, pronouns). We annotate these nodes of interest in the trees.

**Step 6: Tree Simplification (Line 11):** We simplify the annotated trees by removing irrelevant nodes and paths (i.e., removing the trees without any candidate IOC relation verbs or the paths without any IOC nodes). This step does not influence the extraction outcome, but helps speed up the performance.

**Step 7: Coreference Resolution (Line 14):** Across all trees of all sentences within a block, we resolve the coreferenced nodes for the same IOC by checking their POS tags and dependencies, and create connections between the nodes in the trees. After this step, we have a set of final annotated, simplified dependency trees for the OSCTI text.

**Step 8: IOC Scan and Merge (Line 16):** As the same IOC may appear across different blocks in different phrases, we scan all IOCs in the dependency trees of all blocks, and merge similar ones based on both the character-level overlap and the semantic similarity of word vectors (we used word vectors in spaCy [38]). This is different from Step 7, which performs coreference resolution within a block. After this step, we have a set of final IOCs served as nodes in the threat behavior graph.

**Step 9: IOC Relation Extraction (Line 18):** We present the details of our dependency parsing-based IOC relation extraction algorithm: (1) For each dependency tree, we enumerate all pairs of IOCs nodes; (2) Then, for each pair of IOC nodes, we check whether they satisfy the subject-object relation by considering their dependency types in the tree. In particular, we consider three parts of their dependency path: one common path from the root to the LCA (Lowest Common Ancestor); two individual paths from the LCA to each of the nodes, and constructed a set of dependency type rules to do the checking; (3) Next, for the pair that passes the checking, we extract its relation verb by first scanning all the annotated candidate verbs (i.e., annotations are done in Step 5) in the aforementioned three parts of dependency path, and then selecting the one that is closest to the object IOC node; (4) The candidate IOC node pair and the selected verb (after lemmatization) then form the final IOC entity-relation triplet.

**Step 10: Threat Behavior Graph Construction (Line 20):** We iterate over all IOC entity-relation triplets sorted by the occurrence offset of the relation verb in OSCTI text, and construct a threat behavior graph. Each edge in the graph is associated with a sequence number, indicating the step order.

Our evaluations on a wide range of OSCTI texts demonstrate that EFFHUNTER’s threat behavior extraction pipeline is accurate (Section IV-B1) and efficient (Section IV-B3).
be searched. Figure 2 shows an example TBQL query in this syntax that hunts for a data leakage attack.

Specifically, in Grammar 1 the \langle \text{patt} \rangle rule specifies an event pattern, including the subject/object entity (\langle \text{entity} \rangle), the operation (\langle \text{op}_\text{exp} \rangle), the pattern ID (\langle \text{patt}_\text{id} \rangle), and the optional time window (\langle \text{wind} \rangle). The \langle \text{entity} \rangle rule specifies the entity type, the entity ID, and the optional attribute filter expression (\langle \text{attr}_\text{exp} \rangle). Operators (e.g., logical, comparison) are supported in \langle \text{op}_\text{exp} \rangle and \langle \text{attr}_\text{exp} \rangle to form complex expressions (e.g., proc p[pid = 1 && exename = "chrome.exe"] read || write file f, where % matches any character sequence). The \langle \text{wind} \rangle rule specifies a time window that narrows down the search. The \langle \text{global}_\text{filter} \rangle rule specifies the global filters for all event patterns. The \langle \text{rel} \rangle rule specifies the relationship between event patterns. TBQL supports two types of relationships: temporal relationship (e.g., evt1 before[0-5 min] evt2 specifies a temporal order of events), and attribute relationship (e.g., p1.pid = p2.pid specifies that the two processes have the same PID). The \langle \text{return} \rangle rule specifies the attributes of the matched events for return.

In addition, TBQL provides different types of syntactic sugars to facilitate the query construction:

- Default attributes for system entities: default attribute names will be inferred if the user only specifies attribute values in an event pattern, or entity IDs in the \langle \text{return} \rangle clause. We select the most commonly used attributes in security analysis as default attributes: “name” for files, “exename” for processes, and “dstip” for network connections.
- Entity ID reuse: reusing an entity ID in multiple event patterns implicitly indicates that the entities are the same.

For example, in the TBQL query in Figure 2 for hunting data leakage attack, proc pl[exename = "%/bin/tar"] will be inferred as proc pl[exename = "%/etc/passwd"]; file f["%/etc/passwd"] will be inferred as file f[name = "/etc/passwd"]; ip i1["192.168.29.128"] will be inferred as ip i1[dstip = "192.168.29.128"], and return p1 will be inferred as return pl.exename. Besides, the entity ID p1 is used in both evt1 and evt2, indicating the same system entity.

(2) Variable-Length Event Path Pattern Syntax: In addition to the basic event pattern syntax, EffHUNTER provides an advanced syntax that specifies various types of variable-length paths of system event patterns. The \langle \text{op}_\text{path} \rangle rule gives the core syntax, which provides several alternatives:

- proc p \Rightarrow [read] file f: a path of arbitrary length from a process entity p to a file entity f. The operation type of the final hop (i.e., system event where f is an object) is read.
- proc p \Rightarrow (2-4) [read] file f: the path has a minimum length of 2 and a maximum length of 4.
- proc p \Rightarrow (2+) [read] file f: the path has a minimum length of 2. The maximum length is not restricted.
- proc p \Rightarrow (4-) [read] file f: the path has a maximum length of 4. The minimum length is 1.
- proc p \Rightarrow [read] file f: the path has a length of 1. This is semantically equivalent to the basic event pattern syntax, e.g., proc p read file f. The difference lies in the execution: this length-1 event path pattern will be compiled into a Cypher data query executed on the Neo4j database, while the basic event pattern will be compiled into a SQL data query executed on the PostgreSQL database.

- proc p \Rightarrow file f: the operation type of the final hop is omitted, indicating that the search allows any operation type.

This syntax is particularly useful when doing query synthesis: in certain cases, an edge in the threat behavior graph (hence a threat step between two IOCs in OSCTI text) may correspond to a path of system events in system audit logging data. This happens often when intermediate processes are created to chain system events, but are omitted in the OSCTI text by the human writer. For example, for the OSCTI text that mentions “the browser process /usr/bin/firefox reads the password file /etc/passwd”, the constructed threat behavior graph will have an edge “Filepath(/usr/bin/firefox) \rightarrow Filepath(/etc/passwd)”. However, in the system audit logging data, this may correspond to a path where a node representing the “/usr/bin/firefox” process forks additional processes, one of which reads the password file “/etc/passwd”. With the variable-length event path pattern syntax, the information flow between two system entities can be easily specified (e.g., proc p["/usr/bin/firefox"] \Rightarrow [read] file f["/etc/passwd"] for the example scenario) and the semantic gap between the OSCTI text and the system audit logging data can be bridged.

To simplify the presentation, a “TBQL pattern” refers to both an event pattern and a variable-length event path pattern.

E. TBQL Query Synthesis

To facilitate threat hunting with OSCTI, EffHUNTER provides a query synthesis mechanism that automatically synthesizes a TBQL query from the threat behavior graph. Next, we present the mechanism in detail.

Step 1: Pre-Synthesis Screening & IOC Relation Mapping: One challenge in query synthesis is the semantic gap between the types of IOCs and IOC relations, and the types of system entities and their operations. To bridge the gap, EffHUNTER first performs a pre-synthesis screening to filter out nodes (and connected edges) in the threat behavior graph whose associated IOC types are not currently captured by the system auditing component (e.g., registry entries). Then, for each remaining edge, EffHUNTER maps its associated IOC relation to the TBQL operation type (e.g., \langle op \rangle rule in Grammar 1). We constructed a set of rules for IOC relation mapping, which consider both the semantic meaning of the IOC relation and the types of the connected IOC nodes. For example, the “download” relation between two “Filepath” IOCs will be mapped to the “write” operation in TBQL, indicating a process writes data to a file. In contrast, the “download” relation from a “Filepath” IOC to an “IP” IOC will be mapped to the “read” operation in TBQL, indicating a process reads data from a network connection. EffHUNTER further filters out edges whose associated IOC relations do not match any rules.

Step 2: TBQL Pattern Synthesis: For each node in the threat behavior graph, EffHUNTER synthesizes a TBQL system entity (i.e., rule \langle \text{entity} \rangle) and assigns a unique entity ID:
(1) for a source node, EffHunter synthesizes a process entity; (2) for a sink node, EffHunter synthesizes a network connection entity if its associated IOC type is an IP. Otherwise, EffHunter synthesizes either a file entity or a process entity depending on the associated IOC relation of the edge. EffHunter then synthesizes the attribute of the entity using the associated IOC content (file name, file path, IP). Wildcard operators * are added around the attribute string by default.

EffHunter synthesizes a TBQL pattern (i.e., rule (pattern)) by connecting the synthesized TBQL subject & object entities and the mapped TBQL operation. By default, a TBQL event pattern is synthesized. System administrator can pre-configure the system to synthesize a variable-length event path pattern.

Step 3: TBQL Pattern Relationship Synthesis: For TBQL event patterns, EffHunter synthesizes their temporal relationships by following an ascending order of the sequence numbers of corresponding edges in the threat behavior graph. For variable-length event path patterns, this step is omitted since event paths in TBQL do not have temporal relationships.

Step 4: TBQL Return Synthesis: To synthesize the TBQL return clause, EffHunter by default appends all entity IDs to the “return” string. Default attribute names will be inferred when the query is executed and the corresponding attribute values will be returned (i.e., syntactic sugars in Section 3.3D). Figure 2 shows an example TBQL query synthesized using the default synthesis plan. In addition, EffHunter supports user-defined synthesis plans to overwrite the default plan and synthesize other attributes that are supported but not captured in the threat behavior graph (e.g., hostname, time window).

F. TBQL Query Execution

To efficiently execute a TBQL query with many TBQL patterns (could be a mix of event patterns and variable-length event path patterns), EffHunter compiles each TBQL pattern into a semantically equivalent SQL or Cypher data query, and schedules the execution of these data queries in different database backends (i.e., PostgreSQL and Neo4j) by analyzing their estimated pruning power and semantic dependencies. Specifically, for an event pattern, EffHunter compiles it into a SQL data query, so that the mature indexing mechanism and the efficient support for joins in relational databases can be leveraged. The compiled SQL query joins two system entity tables with one system event table, and applies the filters in the WHERE clause. For a variable-length event path pattern, since it is difficult to perform graph pattern search using SQL, EffHunter compiles it into a Cypher data query by leveraging Cypher’s path pattern syntax.40

We now present our data query scheduling algorithm: For each TBQL pattern, EffHunter computes a pruning score by counting the number of constraints declared; a TBQL pattern with more constraints has a higher score. For a variable-length event path pattern, we additionally consider the length of the path when computing the score; a pattern with a smaller maximum path length has a higher score. Then, when scheduling the execution of the data queries, EffHunter considers both the pruning scores and the pattern dependencies: if two TBQL patterns have dependencies (e.g., connected by the same system entity), EffHunter will first execute the data query whose associated pattern has a higher pruning score, and then use the execution results to constrain the execution of the other data query (by adding additional filters). This way, complex TBQL queries with various TBQL patterns can be efficiently executed in different database backends seamlessly.

IV. Evaluation

We built EffHunter (~ 25K LOC) upon several tools: Sysdig30 for system auditing, PostgreSQL31 and Neo4j32 for system audit logging data storage, Python and spaCy33 for threat behavior extraction, ANTLR 441 for TBQL language parser, and Java for the whole system.

We deployed EffHunter on a physical testbed to collect real system audit logs and hunt for malicious behaviors. We evaluated various aspects of EffHunter on a broad set of attack cases. In total, the audit logs used in our evaluations contain 47,688,033 system entities (2,499,051 files, 40,392,472 processes, 4,796,510 network connections) and 55,840,381 system events (20,133,944 file events, 27,951,142 process events, 7,755,295 network events). Our evaluations aim to answer the following research questions:

- **RQ1**: How accurate is EffHunter in extracting threat behaviors from OSCTI text compared to general information extraction approaches?
- **RQ2**: How accurate is EffHunter in finding malicious system activities using OSCTI text?
- **RQ3**: How efficient is EffHunter in extracting threat behaviors from OSCTI text, constructing a threat behavior graph, and synthesizing a TBQL query?
- **RQ4**: How efficient is EffHunter in executing TBQL queries over the big system audit logging data?
- **RQ5**: How concise is TBQL in specifying malicious system behaviors compared to general-purpose query languages?

RQ1 aims to evaluate the accuracy of EffHunter in threat behavior extraction. RQ2 aims to evaluate the end-to-end accuracy of EffHunter in threat hunting using OSCTI. RQ3 aims to evaluate the efficiency of EffHunter in threat behavior extraction, threat behavior graph construction, and TBQL query synthesis. RQ4 aims to evaluate the efficiency of EffHunter in TBQL query execution, and measure the performance speedup achieved by the TBQL query scheduler in different database backends. RQ5 aims to evaluate the conciseness of TBQL in expressing complex system behaviors.

A. Evaluation Setup

The deployed server has an Intel(R) Xeon(R) CPU E5-2637 v4 (3.50GHz), 256GB RAM running 64bit Ubuntu 18.04.1. The server is frequently used by > 15 active users to perform various daily tasks, including file manipulation, text editing, and software development. To evaluate EffHunter, we constructed an evaluation benchmark comprising 18 attack cases: 15 cases released in the DARPA TC dataset42, and 3 multi-step intrusive attacks that we performed on the deployed server based on the Cyber Kill Chain framework34 and
TABLE IV: 18 attack cases used in evaluations

| Case ID       | Case Name                                      |
|--------------|------------------------------------------------|
| tc_cleanScope_1| 20180406 1500 ClearScope – Phishing E-mail Link |
| tc_cleanScope_2| 20180411 1400 ClearScope – Firefox Backdoor w/ Drakon In-Memory |
| tc_cleanScope_3| 20180413 ClearScope                           |
| tc_fivedirections_1| 20180409 1500 FiveDirections – Phishing E-mail w/ Excel Macro |
| tc_fivedirections_2| 20180411 1000 FiveDirections – Firefox Backdoor w/ Drakon In-Memory |
| tc_fivedirections_3| 20180412 1100 FiveDirections – Browser Extension w/ Drakon Dropper |
| tc_theia_1    | 20180410 1400 THEIA – Firefox Backdoor w/ Drakon In-Memory |
| tc_theia_2    | 20180410 1300 THEIA - Phishing Email w/ Link |
| tc_theia_3    | 20180412 1000 THEIA - Browser Extension w/ Drakon Dropper |
| tc_theia_4    | 20180413 1400 THEIA - Phishing E-mail w/ Executable Attachment |
| tc_trace_1    | 20180410 1000 TRACE – Firefox Backdoor w/ Drakon In-Memory |
| tc_trace_2    | 20180410 1200 TRACE – Phishing E-mail Link |
| tc_trace_3    | 20180412 1300 TRACE – Browser Extension w/ Drakon Dropper |
| tc_trace_4    | 20180413 1200 TRACE – Pine Backdoor w/ Drakon Dropper |
| tc_trace_5    | 20180413 1400 TRACE – Phishing E-mail w/ Executable Attachment |
| password_crack| Password Cracking After Shellshock Penetration |
| data_leak     | Data Leakage After Shellshock Penetration |
| vpnfilter     | VPNFilter                                      |

CWE [35]. When we perform the attacks and conduct the evaluations, the sever continues to serve other users. This setup ensures that enough noise of benign background traffic is collected in together with malicious activities, representing the real-world deployment. Furthermore, benign activities significantly outnumber attack activities (55 million vs. thousands), demonstrating the challenge in threat hunting. Table IV shows the complete list of 18 attack cases.

1) DARPA TC Attack Cases: We selected 15 cases from the DARPA TC Engagement 3 data release [42], which cover various combinations of OSs (e.g., Linux, Windows, Android), vulnerabilities (e.g., Nginx backdoor, Firefox backdoor, browser extension), and exploits (e.g., Drakon APT, micro APT, phishing email with malicious Excel attachment).

Specifically, the dataset consists of the captured audit logs of six performer systems (ClearScope, FiveDirections, THEIA, TRACE, CADETS, and TA5.2) under the penetration of the red team using different attack strategies, which include both benign and malicious system activities. The dataset also includes a ground-truth report that has attack descriptions for the cases. We examined the audit logs, and found out that the data for TA5.2 is missing and the data for CADETS lacks key attributes (e.g., file name, process executable name). Thus, we do not consider the cases for these two systems in our evaluations. Nevertheless, same or very similar attacks were performed for other performer systems and are considered in our evaluations. For the other four performer systems, we selected all the attack cases (15 in total) in our evaluation benchmark. For each case, we parsed the provided audit logs and loaded the data in EffHUNTER’s databases. We then extracted the attack description text from the ground-truth report and use the text as input to EffHUNTER.

2) Multi-Step Intrusive Attack Cases: To increase the coverage of our evaluation benchmark, we further constructed 3 multi-step intrusive attack cases. These cases were constructed based on CVE [35] and capture the important traits of attacks depicted in the Cyber Kill Chain framework [34] (e.g., including the stages of initial penetration, data exfiltration). We performed these attacks on the deployed server and collected system audit logs. The attack description texts were constructed according to the way the attacks were performed.

Attack 1: Password Cracking After Shellshock Penetration. The attacker penetrates into the victim host (i.e., the deployed server) by exploiting the Shellshock vulnerability [43]. After the penetration, the attacker first connects to cloud services (e.g., Dropbox) and downloads an image where C2 (Command and Control) server’s IP address is encoded in the EXIF metadata. This behavior is a common practice shared by APT attacks [44] to evade the network-based detection system based on DNS blacklisting. Based on the IP, the attacker downloads a password cracker from the C2 server to the victim host. The attacker then runs the password cracker against password shadow files to extract clear text.

Attack 2: Data Leakage After Shellshock Penetration. After the previous reconnaissance, the attacker attempts to steal all the valuable assets from the victim host. This stage mainly involves the behaviors of local and remote file system scanning activities, copying and compressing of important files, and transferring the files to the C2 server. The attacker scans the file system, scrapes files into a single compressed file, and transfers it back to the C2 server.

Attack 3: VPNFilter. At this stage, the attacker seeks to maintain a direct connection to the victim host from the C2 server. The attacker utilizes the notorious VPNFilter malware [45] which infected millions of IoT devices by exploiting a number of known or zero-day vulnerabilities. After the initial penetration on the victim host, the attacker downloads the VPNFilter stage 1 malware from the C2 server, which accesses a public image repository to get an image. In the EXIF metadata of the image, the IP address for the stage 2 server is encoded. The stage 1 malware then downloads the VPNFilter stage 2 malware from the stage 2 server, and executes it to launch the VPNFilter attack, which establishes a direct connection to the C2 server.

B. Evaluation Results

1) RQ1: Accuracy of Threat Behavior Extraction: To evaluate the accuracy of EffHUNTER in extracting threat behaviors from OSCTI text, we labeled the OSCTI texts based on the ground truth and measure the precision, recall, and F1 score of the extracted IOC entities and IOC relations. We compare EffHUNTER with two state-of-the-art open information extraction (Open IE) approaches that are widely used to extract entities and relations from general-purpose text (e.g., news articles): Stanford Open IE [25] and Open IE 5 [26]. Furthermore, we are interested in studying the effect of IOC Protection on the IOC entity and IOC relation extraction accuracy. Thus, we also compare EffHUNTER with the version of EffHUNTER without IOC Protection, Stanford Open IE with IOC Protection, and Open IE 5 with IOC Protection.

Table V shows the precision, recall, and F1 score of all compared approaches, aggregated over all evaluation cases. The detailed TP/TN/FP/FN counts for individual cases are available on our project website [33]. We have the following observations: (1) EffHUNTER achieves the highest precision, recall, and F1 score for both IOC entity extraction and IOC relation extraction among all compared approaches. In particular, EffHUNTER has 96.64% F1 for IOC entity extraction and...
have the following observations: (1) E

Table VI shows the precision and recall of all cases. We ground-truth system events that are related to the attack. The event patterns in the synthesized TBQL query, and the end-to-end accuracy of E

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instead of threat behavior extraction from OSCTI text, their approaches target general open information extraction in improving the accuracy of other NLP components. Though, this again demonstrates the effectiveness of IOC Protection in protecting the security context of texts, achieving 100% precision, 96.74% recall, and 98.34% F1. This is largely due to the high accuracy achieved by E

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threat behavior extraction pipeline; (2) Though some excessive event patterns may be occasionally synthesized (e.g., in password_crack, one excessive event pattern is synthesized: proc p3["%/tmp/libfoo.so%"] write file f2 ["%/tmp/john.zip%" as evt5]), the design of E

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demonstrates the effectiveness of IOC Protection ensures that these excessive event patterns will rarely retrieve benign activities. The reason is because these excessive patterns have IOCs as subject/object constraints, which are extracted by a set of highly-precise regex rules in E

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As a result, very few benign activities are falsely retrieved (e.g., 0 false positive rate in our evaluation benchmark); (3) For queries that have false negatives, the primary reason is due to the semantic ambiguity in query synthesis for certain IOC relations. For example, in tc_trace_1, there is an edge pointing from the “Filepath” IOC “/home/admin/cache” to itself with the “run” relation. Both the IOC and the relation are corrected extracted from OSCTI text. However, when performing query synthesis, there is no way to differentiate whether it represents a file event proc p1["%/home/admin/cache %"] execute file f1["%/home/admin/cache%"] or a process event proc p1["%/home/admin/cache%") start proc p2["%/home/admin/cache%"], as both events are related to process creation. The default synthesis plan in E

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synthesizes the first pattern, while for this case, the second pattern has matched ground-truth system events. As a result, 37 system events are missed. One way to mitigate this is to let the security analyst revise the query to improve the coverage, and the synthesized event patterns serve as a base for exploration.

It is worth mentioning that the three cases for ClearScope were conducted on Android OS and the ground-truth system events have Android package names as process executable names (e.g., proc p1["com.android.defcontainer %"] open file f1["%/MsgApp-instr.apk%"]), which are different from other cases in which process executables are normal Linux/Windows files. Nevertheless, E

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is able to accurately extract such information from OSCTI text and use the information to find the malicious system events, thanks to the coverage of a wide range of IOC types and IOC relations in E

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’s threat behavior extraction pipeline.

3) RQ3: Efficiency of Threat Behavior Extraction: Table VII shows the execution time (second) of different stages of E

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: threat behavior extraction, threat behavior graph construction, and TBQL query synthesis. For threat behavior extraction, we also compare with other baseline approaches. We have the following observations: (1)
EFFHUNTER is very efficient in processing the input OSCTI texts, constructing threat behavior graphs, and synthesizing TBQL queries. The average time for the three stages is 0.52s; (2) Stanford Open IE and Open IE 5 are more expensive in extracting threat behaviors compared to EFFHUNTER (0.70s and 13.46s vs. 0.42s), since these general information extraction approaches also spend a long time analyzing texts that are unrelated to threat behaviors; (3) IOC Protection adds trivial overhead to the threat behavior extraction stage.

4) RQ4: Efficiency of TBQL Query Execution: We measure the runtime performance of EFFHUNTER in executing TBQL queries, particularly the performance speedup provided by the TBQL query scheduler in different database backends. To prepare for evaluation, for each case, we construct four types of semantically equivalent queries according to the corresponding synthesized TBQL query by EFFHUNTER:

(a) TBQL query using the event pattern syntax (e.g., `proc p open file f as evt`).

(b) SQL query that encodes all event patterns and filters in the FROM and WHERE clauses.

(c) TBQL query using the length-1 event path pattern syntax (e.g., `proc p ->[open] file f as evt`).

(d) Cypher query that encodes all length-1 event path patterns and filters in the MATCH and WHERE clauses.

All these four types queries are semantically equivalent; they search for the same system behaviors and return the same results. The difference lies in the query scheduler and the database backend: Queries (a) and (b) are executed in PostgreSQL, and Queries (c) and (d) are executed in Neo4j. Besides, Queries (a) and (c) benefit from optimizations in TBQL query scheduler, and Queries (b) and (d) do not.

Table VIII shows the execution time (in second) of the four types of queries. For each query, we measure its execution time for 20 rounds and record the mean and the standard deviation. We have the following observations: (1) TBQL query scheduler provided by EFFHUNTER is generally more efficient than the query schedulers provided by PostgreSQL and Neo4j. Specifically, for PostgreSQL backend, EFFHUNTER is 3810.17/168.18 = 22.7x faster; for Neo4j backend, EFFHUNTER is 3104.68/343.04 = 9.1x faster; (2) There also exist a few cases in which TBQL queries run slightly slower than SQL queries and Cypher queries. Particularly, when the TBQL query only contains 1 pattern (i.e., `tc_clearscope_3`, `tc_trance_3`), TBQL query runs slower than SQL query and Cypher query as additional time is taken to parse the TBQL query and compile into SQL or Cypher data queries. When the number of patterns becomes large, SQL queries and Cypher queries become much slower (e.g., `data_leak`), as these giant queries have many joins and constraints mixed together, which may suffer from indeterministic optimizations and take long to finish execution; (3) PostgreSQL is generally faster than Neo4j, as relational databases have mature indexing mechanisms and better support for joins; (4) The standard deviation is small compared to the mean. This indicates that the 20-round mean values are representative of the runtime performance of different types of queries in the deployed environment. These results demonstrate the superiority of TBQL query scheduler in speeding up the execution of TBQL queries in different database backends.

5) RQ5: Conciseness of TBQL: For the four types of queries mentioned in RQ4, we further compare their conciseness by measuring the number of characters (excluding spaces and comments) and words. Table IX shows the results. We observe that: (1) TBQL is more concise than SQL and Cypher for all cases. Specifically, for # characters, TBQL is 15007/4460 = 3.4x more concise than SQL and 13601/4772 = 2.9x more concise than Cypher; for # words, TBQL is 2670/945 = 2.8x more concise than SQL and 2113/968 = 2.2x more concise than Cypher. This is because TBQL directly models the high-level, domain-specific concepts like system entities and system events, instead of the low-level concepts like tables or nodes/relationships; (2) The conciseness saving of TBQL compared to SQL and Cypher increases when more patterns are declared (e.g., `pass-word_crack`, `data_leak`); (3) Cypher queries are generally more concise than SQL queries. This is within our expectation as Cypher has a concise syntax to specify linked nodes and relationships, while SQL models everything as tables and has to explicitly specify table joins to represent system events.

V. DISCUSSION

Limitations. As mentioned in Section II, attacks on OS kernels, system auditing frameworks, and databases, and attacks that are not captured by system auditing (e.g., side channel attacks, memory-based attacks) are not considered by
EffHUNTER. Besides, EffHUNTER's end-to-end pipeline is not applicable or will have limited performance if the OSCTI text for the attack is not available, is compromised, or contains little useful information (e.g., no IOCs, no sentence structures that contain IOC relations). In such cases, the TBQL query subsystem of EffHUNTER can be used as a standalone tool for proactive threat hunting, and the security analyst can manually construct TBQL queries and iterate over the execution results.

Design Alternatives. EffHUNTER currently leverages regex rules to extract IOCs. Besides IOCs, other types of entities may also exist in OSCTI text that constitute threat behaviors, such as threat actors (e.g., CozyDuke [46]) and tools (e.g., Mimikatz [47]), which are hard to extract using fixed regex rules. To extend the support for these types of entities, one approach is to adopt learning-based methods to perform Named Entity Recognition (NER) [48]. Different from EffHUNTER's current NLP pipeline, NER approaches are supervised and have a pre-synthesis screening step to filter out nodes in the threat behavior graph that contain IOC relations. In such cases, the TBQL query language provided in EffHUNTER is different from these works, as none of these works proposed to facilitate threat hunting via automated extraction of threat behaviors from OSCTI text and automated synthesis of threat hunting queries using the extracted threat behaviors. Besides, the TBQL query language provided in EffHUNTER has a set of features particularly designed for threat hunting (e.g., variable-length event path pattern syntax) that are not supported in prior query tools [10]–[13].

In future work, we plan to expand our monitoring scope by including more types of entities and events, such as Windows registry entries and Linux pipes.

### VI. Related Work

In this section, we survey three categories of related work.

**Forensic Analysis via System Audit Logs.** Research progress has been made to leverage system audit logs for forensic analysis. Causality analysis based on system audit logging data plays a critical role in identifying root causes and ramifications of attacks [4], [5]. Recent efforts have been made to mitigate the dependency explosion problem by performing fine-grained causality analysis [7], [8], prioritizing dependencies [9], and reducing data size [6], [27]. Besides, research has proposed to query system audit logging data for attack investigation and anomaly detection [10]–[13]. The scope of EffHUNTER is different from these works, as none of these works proposed to facilitate threat hunting via automated extraction of threat behaviors from OSCTI text and automated synthesis of threat hunting queries using the extracted threat behaviors. Besides, the TBQL query language provided in EffHUNTER has a set of features particularly designed for threat hunting (e.g., variable-length event path pattern syntax) that are not supported in prior query tools [10]–[13].

**OSCTI Analysis and Management.** Research progress has been made for automated OSCTI analysis, including extracting IOCs [49], extracting vulnerable products and vulnerability terms from NVD descriptions [50], extracting threat action...
terms from semi-structured Symantec reports [51], understanding vulnerability reproducibility [52], and measuring information inconsistency [53]. EffHUNTER distinguishes from all these works in the sense that it seeks to extract both IOCs and IOC relations from unstructured OSCTI text, which is a problem that has not been studied before. Furthermore, EffHUNTER seeks to leverage the extracted threat information to facilitate threat hunting, which is the first work in this space.

There also exist platforms and standards for OSCTI management and exchange [19]–[21], [54], [55]. These solutions do not target automated threat behavior extraction from OSCTI text or threat hunting, and are orthogonal to EffHUNTER.

Open Information Extraction. Information extraction (IE) extracts structured information from unstructured natural language text. Open information extraction (Open IE) is a new paradigm of IE that is not limited to a restricted set of target relations known in advance, but rather extracts all types of relations found in the text. Research has proposed to leverage rule-based approaches or learning-based approaches for more accurate Open IE [24]–[26]. EffHUNTER distinguishes from these works in the sense that it focuses on threat behavior extraction from OSCTI text, which requires special designs to handle massive nuances particular to the security domain.

VII. CONCLUSION

We have proposed EffHUNTER, a system that enables efficient cyber threat hunting via extracting threat behaviors from OSCTI text and querying the extracted behaviors from system audit logs. Evaluations on a wide range of attack cases demonstrate the practical efficacy of EffHUNTER in using OSCTI for cyber threat hunting.

REFERENCES

[1] “Target Data Breach Incident,” http://www.nytimes.com/2014/02/27/business/target-reports-on-fourth-quarter-earnings.html?_r=1
[2] “Yahoo discloses hack of 1 billion accounts,” https://techcrunch.com/2016/12/14/yahoo-discloses-hack-of-1-billion-accounts/
[3] “The Equifax Data Breach,” https://www.ftc.gov/equifax-data-breach.
[4] S. T. King and P. M. Chen, “Backtracking intrusions,” in SOSP, 2003.
[5] S. T. King, Z. M. Mao, D. G. Lucchetti, and P. M. Chen, “Enriching intrusion alerts through multi-host causality,” in NDSS, 2005.
[6] K. H. Lee, X. Zhang, and D. Xu, “Loggc: garbage collecting audit log,” in CCS, 2013.
[7] ——, “High accuracy attack provenance via binary-based execution partition,” in NDSS, 2013.
[8] S. Ma, X. Zhang, and D. Xu, “Protracer: towards practical provenance tracing by alternating between logging and tainting,” in NDSS, 2016.
[9] Y. Liu, M. Zhang, D. Li, K. Jee, Z. Li, Z. Wu, J. Rhee, and P. Mittal, “Towards a timely causality analysis for enterprise security,” in NDSS, 2018.
[10] P. Gao, X. Xiao, Z. Li, F. Xu, S. R. Kulkarni, and P. Mittal, “AIQL: Enabling efficient attack investigation from system monitoring data,” in USENIX ATC, 2018.
[11] P. Gao, X. Xiao, D. Li, Z. Li, K. Jee, Z. Wu, C. H. Kim, S. R. Kulkarni, and P. Mittal, “SAQL: A stream-based query system for real-time abnormal system behavior detection,” in USENIX, 2018.
[12] T. Pasquier, X. Han, T. Moyer, A. Bates, O. Hermant, D. Eyers, J. Bacon, and M. Seltzer, “Runtime Analysis of Whole-System Provenance,” in CCS, 2018.
[13] X. Shu, F. Araujo, D. L. Schales, M. P. Stoelcklin, J. Jang, H. Huang, and J. R. Rao, “Threat intelligence computing,” in CCS, 2018.
[14] “Splunk Search Processing Language,” https://www.splunk.com/en_us/resources/search-processing-language.html.
[15] “Elastic SIEM,” https://www.elastic.co/siem.
[16] “Open Source Threat Intelligence Feeds,” https://www.senki.org/operators-security-toolkit/open-source-threat-intelligence-feeds.
[17] “PhishTank,” https://www.phishTank.com.
[18] “OpenPhish,” https://www.openphish.com/.
[19] “Structured Threat Information eXpression,” http://stixproject.github.io/.
[20] “MISP - Open Source Threat Intelligence Platform & Open Standards For Threat Information Sharing,” https://www.misp-project.org/.
[21] “The History of OpenIOC,” https://www.fireeye.com/blog/threat-research/2013/09/history-openioc.html.
[22] “AlienVault,” https://www.alienvault.com/blogs/labresearch/
[23] “SecureList,” https://securelist.com/
[24] A. Yates, M. Banko, M. Broadhead, M. J. Cafarella, O. Etzioni, and S. Soderland, “Textrunner: open information extraction on the web,” in NAACL-HLT, 2007.
[25] G. Angeli, M. J. Premkumar, and C. D. Manning, “Leveraging linguistic structure for open domain information extraction,” in ACL, 2015.
[26] “Open IE 5,” https://github.com/dair-itd/OpenIE-standalone
[27] Z. Xu, Z. Wu, Z. Li, K. Jee, J. Rhee, X. Xiao, F. Xu, H. Wang, and G. Jiang, “High fidelity data reduction for big data security dependency analyses,” in CCS, 2016.
[28] “The Linux Audit Framework,” https://github.com/linux-audit/
[29] “ETW events in the common language runtime,” https://msdn.microsoft.com/en-us/library/hf357190(v=vs.110).aspx.
[30] “Sysdig,” http://www.sysdig.org/
[31] “PostgreSQL,” http://www.postgresql.org/
[32] “Neo4j,” http://neo4j.com/
[33] “EffHUNTER Website,” https://sites.google.com/site/effhuntersystem/
[34] “Cyber Kill Chain,” http://www.lockheedmartin.com/us/what-we-do/information-technology/cybersecurity/tradecraft/cyber-kill-chain.
[35] “Common Vulnerabilities and Exposures,” https://cve.mitre.org.
[36] A. M. Bates, D. Tian, K. R. B. Butler, and T. Moyer “Trustworthy whole-system provenance for the linux kernel,” in USENIX Security, 2015.
[37] “ioc-parser,” https://github.com/arnibues/ioc_parser
[38] “spaCy,” https://spacy.io/usage/linguistic-features
[39] “SQL: Structured Query Language,” https://www.iso.org/iso/catalogue_detail.htm?csnumber=45978
[40] “Cypher Query Language,” http://neo4j.com/developer/cypher/
[41] “ANTLR,” http://www.antlr.org/
[42] “Transparent computing engagement 3 data release,” https://github.com/darpa-12o/Transparent-Computing/blob/master/README.Ev3.md
[43] “CVE-2014-6271: bash: specially-crafted environment variables can be used to inject shell commands.” https://cve.mitre.org/cgi-bin/cvename.cgi?name=CVE-2014-6271
[44] “VPNFilter: New Router Malware with Destructive Capabilities,” https://symantec-enterprise-blogs.security.com/security/threat-intelligence/vpnfilter-iot-malware
[45] “Router Vulnerability and the VPNFilter Botnet,” https://www.schneier.com/blog/archives/2016/06/router_vulnerab.html.
[46] “APT1,” https://attack.mitre.org/groups/G0016/
[47] “Mimikatz,” https://attack.mitre.org/software/S0002/
[48] G. Lamble, M. Ballesteros, S. Subramanian, K. Kawakami, and C. Dyer, “Neural architectures for named entity recognition,” in NAACL-HLT, 2016.
[49] X. Liao, K. Yuan, X. Wang, Z. Li, L. Xing, and R. Beyah, “Acing the ioc game: Toward automatic discovery and analysis of open-source cyber threat intelligence,” in CCS, 2016.
[50] A. Joshi, R. Lal, T. Finin, and A. Joshi, “Extracting cybersecurity related linked data from text,” in IJCS, 2013.
[51] G. Husari, E. Al-Shaer, M. Ahmed, B. Chu, and X. Niu, “Tfpdrill: Automatic and accurate extraction of threat actions from unstructured text of cti sources,” in ACSAC, 2017.
[52] D. Mu, A. Cuevas, L. Yang, H. Hu, X. Xing, B. Mao, and G. Wang, “Understanding the reproducibility of crowd-reported security vulnerabilities,” in USENIX Security, 2018.
[53] Y. Dong, W. Guo, Y. Chen, X. Xing, Y. Zhang, and G. Wang, “Towards the detection of inconsistencies in public security vulnerability reports,” in USENIX Security, 2019.
[54] “ThreatCrowd,” https://www.threatcrowd.org/.