Abstract

System auditing is a vital technique for collecting system call events as system provenance and investigating complex multi-step attacks such as Advanced Persistent Threats. However, existing attack investigation methods struggle to uncover long attack sequences due to the massive volume of system provenance data and their inability to focus on attack-relevant parts. In this paper, we present Raptor, a defense system that enables human analysts to effectively analyze large-scale system provenance to reveal multi-step attack sequences. Raptor introduces an expressive domain-specific language, ProvQL, that offers essential primitives for various types of attack analyses (e.g., attack pattern search, attack dependency tracking) with user-defined constraints, enabling analysts to focus on attack-relevant parts and iteratively sift through the large provenance data. Moreover, Raptor provides an optimized execution engine for efficient language execution. Our extensive evaluations on a wide range of attack scenarios demonstrate the practical effectiveness of Raptor in facilitating timely attack investigation.

1 INTRODUCTION

Despite significant increases in spending on operations security, the frequency of modern targeted cyberattacks, such as Advanced Persistent Threats (APTs), continues to rise. Unlike traditional threats, these attacks are highly sophisticated, leveraging multiple vulnerabilities to infiltrate the system and exfiltrate sensitive data through a series of steps [47]. Consequently, many high-profile businesses have suffered massive data breaches and huge financial losses [2, 15, 19].

To counter these intrusive multi-step attacks, ubiquitous system auditing has emerged as a vital approach for monitoring attack footprints [16]. System auditing monitors system call events between system entities as system audit logs. Unlike application-level monitoring (e.g., Apache server logging), which only provides limited knowledge about specific applications and generates logs in different formats, system auditing is not tied to applications and generates audit logs with a consistent structure. The collected audit logs further enable the construction of a system provenance graph [35], in which nodes represent system entities (e.g., processes, files, network sockets) and edges represent system call events (e.g., a process writes to a file). A system provenance graph provides a holistic view of all the activities in the system, which is particularly useful for investigating cyber attacks and uncovering attack steps [37, 43]. However, system auditing produces a huge amount of daily logs (e.g., 0.5 GB ∼ 1 GB for one enterprise host [52]), resulting in a giant provenance graph. Additionally, the complexity of multi-step attacks poses significant challenges to existing system provenance-based defenses, which struggle to effectively uncover long attack sequences within such large provenance graphs.

Existing provenance-based attack investigation approaches often leverage causal dependency tracking [32, 37–40, 43, 44]. These approaches model the control/data flow dependencies between system entities in a system event, track the dependencies from a Point-Of-Interest (POI) event (e.g., an alert event like a process creating a suspicious file), and construct a dependency graph, which is a subgraph of the whole system provenance graph. Security analysts can inspect the dependency graph to reveal the attack sequence by reconstructing the chain of events that lead to the POI event. However, due to the lack of fine-grained user control of the tracking process, these approaches suffer from dependency explosion: the generated dependency graph is gigantic (containing >100K edges) and contains many system events that are irrelevant to the attack (e.g., events that load irrelevant system libraries). The problem is worse for multi-step attacks with long attack sequences, making it hard for security analysts to sift through the graph and identify the attack-relevant parts. Fig. 1 shows the dependency graph of a multi-stage data leakage attack and illustrates this problem: a small number of attack-relevant events are buried in an overwhelmingly large number of irrelevant events.

Goal and challenges. We aim to design and build a new defense system that (1) effectively filters out irrelevant system events and reveals complex attack sequences, and (2) efficiently analyzes large-scale system provenance data for a timely investigation. As reported by many security vendors in their annual threat reports [4, 8], human-in-the-loop security emerges as an important paradigm for attack investigation. Humans bring unique strengths to cybersecurity, such as the ability to interpret subtle patterns, understand context, and make nuanced decisions that are difficult for automated systems alone. Such domain knowledge on expected system behaviors and malicious event patterns is crucial for filtering out irrelevant events and reducing dependency explosion as attacks become more sophisticated. Besides, attack investigation is an iterative process that involves multiple rounds of data exploration. An effective defense should provide a flexible and expressive interface for human analysts to incorporate the knowledge and customize the defenses for various attacks.

While several defenses have attempted to identify attack-relevant events from system provenance graphs, they have notable limitations. Multiple approaches seek to enhance dependency tracking fidelity through algorithms based on heuristic rules [32, 34, 43], which can lead to information loss, or through binary instrumentation and kernel customization [39, 44], which introduce intrusive system changes and hinder wide adoption. Several other works aim...
to detect malicious activities through subgraph matching, employing non-learning-based [46] and learning-based [30, 50] techniques. However, these approaches are computationally expensive, requiring extensive offline model training or incurring high runtime overhead over large provenance graphs. Learning-based methods also face generalization challenges, as their models can quickly become outdated with evolving system behaviors. Moreover, existing approaches overlook the importance of human-in-the-loop investigation, lacking flexible and efficient mechanisms to incorporate expert knowledge iteratively. Most methods assume investigations can be completed in a single round, providing limited support for step-by-step inquiries—an essential process for thoroughly investigating complex attacks.

Contributions. In this work, we take an orthogonal approach to existing solutions. We introduce RAPTOR (~15K LOC), a system that facilitates practical investigation of multi-step attacks through efficient human-in-the-loop provenance analysis. RAPTOR leverages system auditing frameworks for provenance collection and databases for data storage. Its core contribution lies in the design and implementation of a powerful domain-specific language (DSL), called System Provenance Query Language (ProvQL), which enables iterative, human-in-the-loop investigations over large-scale system provenance data. ProvQL treats system entities and events as first-class citizens and offers two primary query syntaxes for key investigative tasks: (1) attack pattern search: searching for complex event patterns indicative of malicious behaviors; (2) attack dependency tracking: tracking causal dependencies between events to uncover attack sequences and entry points. ProvQL provides rich constructs that allow users to constraint the search and tracking space to focus on critical parts while filtering out noise, mitigating dependency explosion.

ProvQL is specially designed for attack investigation and is expressive and intuitive to use. With its high-level, declarative syntax, ProvQL abstracts away the low-level complexities of data storage across different backends, enabling security analysts to focus on core attack behaviors rather than low-level details such as table joins. The two syntaxes offer complementary capabilities. Search queries help locate potential suspects (e.g., POI events) for tracking and identify malicious events without dependencies. Tracking queries can uncover long dependency chains that search queries cannot express. To further facilitate iterative investigations, ProvQL allows intermediate query results to be bound to variables and reused in subsequent queries, enabling analysts to refine their findings progressively.

Attack investigation is a time-critical mission to prevent further damage [43]. To efficiently execute ProvQL queries over large provenance data, RAPTOR employs an optimized query scheduling algorithm that decomposes the ProvQL query into small data queries and schedules their execution based on their pruning power, semantic dependencies, and domain data characteristics. RAPTOR also features an in-memory management mechanism that maintains intermediate results bound to variables in in-memory graphs for subsequent manipulations and querying. Queries executing in this mode are much faster, enhancing the efficiency of iterative attack investigations.

Evaluation. We deployed RAPTOR on a testbed and extensively evaluated its effectiveness in reducing dependency explosion, uncovering attack sequences, and executing ProvQL queries efficiently. Additionally, we assessed ProvQL’s usability and effectiveness through a user study. To conduct a thorough evaluation, we built a comprehensive benchmark by executing a wide range of attack scenarios on our testbed and collecting millions of real system events. We compared RAPTOR with multiple baselines, including state-of-the-art provenance-based attack investigation methods (BackTracker [37], PrioTracker [43], DepImpact [32]), general-purpose query languages (SQL [9], Cypher [6]), and a widely used industry attack investigation solution (Splunk [28]).

The evaluation results demonstrate that: (1) RAPTOR can accurately reveal the attack sequence in all attack scenarios while largely reducing the dependency explosion, achieving 0.8766 F1-score and 58.991× graph reduction rate. This significantly outperforms existing defenses: BackTracker, PrioTracker, and DepImpact have only 0.2552, 0.2526, and 0.2604 F1-score, and 9×, 42×, and 24× reduction rate, respectively. (2) RAPTOR can efficiently execute ProvQL queries over massive system provenance. Thanks to the optimizations provided by our query scheduler and in-memory management, ProvQL queries are 4.06× faster than SQL and 56.18× faster than Cypher. (3) ProvQL is much more concise than SQL, Cypher, and Splunk. (4) Our user study confirms ProvQL’s advantages to streamline investigation workflows, reduce cognitive load, and enhance the user experience. These results demonstrate that RAPTOR significantly outperforms existing approaches in combating sophisticated attacks. We open-sourced RAPTOR at [27]. We also developed a UI and created a demo video [22] and a project website [26].

2 BACKGROUND AND MOTIVATING EXAMPLE

Causal dependency tracking. Causal dependency tracking infers dependencies of system events and presents the dependencies as a directed dependency graph. In the dependency graph \( G(V, E) \), a node \( v \in V \) denotes a system entity (e.g., process, file, or network socket). An edge \( e(u, v) \in E \) denotes a system event that involves two entities \( u \) and \( v \) (e.g., process creation, file read or write, and network access). Edge direction (from source node \( u \) to sink node \( v \)) indicates the direction of the information flow. For example, for a process reading data from a file, the file is the source and the process is the sink. For a process writing data to a file, the process is the source and the file is the sink. Each edge \( e(u, v) \) is associated with a time window, \([ts(e), te(e)]\), where \( ts(e) \) and \( te(e) \) denote the start time and the end time of the event \( e \). We adopt the definition consistent with previous studies [32, 37–40, 43, 44] to infer edge directions for different systems calls and event causal dependencies. Formally, for two events \( e_1(u_1, v_1) \) and \( e_2(u_2, v_2) \) (suppose \( e_1 \) occurs earlier than \( e_2 \)), they have causal dependency if \( v_1 = u_2 \) and \( ts(e_1) < te(e_2) \).

Causal dependency tracking, proposed in BackTracker [37], enables two important security analyses: (1) backward tracking that identifies entry points of an attack, and (2) forward tracking that investigates ramifications of an attack. Given a POI event \( e_{poi}(u, v) \), a backward tracking traces back from the source node \( u \) to find all events that have causal dependency on \( u \), and a forward tracking
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Fig. 1: System dependency graphs for a multi-stage, multi-host data leakage attack. The combined dependency graphs of the two victim hosts contain 100, 524 nodes and 154, 353 edges. The attack-relevant nodes and edges, highlighted in dark black, comprise only 20 nodes and 20 edges, indicating the significant challenge of finding “a needle in a haystack”.

traces forward from the sink node ε to find all events on which ε has causal dependency. The output of backward/forward tracking is a backward/forward dependency graph. Take backward tracking as an example. Starting from an empty queue Q and an empty graph G, we first add the POI event to Q and G. Then, we iteratively remove an event ε from Q, find other events that have dependencies on ε, and add these events to Q and G. We repeat this process until Q becomes empty, and the final G is the output backward dependency graph. A major challenge in dependency tracking is dependency explosion. While several subsequent studies [32, 34, 39, 43, 44] have proposed methods to alleviate this issue, these approaches fall short in practical adoption (discussed in Section 9). As shown in Section 7.2, the dependency graphs produced remain excessively large and often miss critical attack-relevant events.

Motivating example. Fig. 1 shows an example multi-stage data leakage attack across three hosts (one attacker host, two victim hosts Host 1 and 2), constructed based on Cyber Kill Chain framework [5] and CVE [3]. The attacker (20.69.152.188) identifies a victim Host 1 (13.66.254.172) in an enterprise network that is vulnerable to the lighttpd Shellshock [18] exploit. To steal data from the victim Host 1, the attacker launches a series of attack steps divided into four stages: (1) Stage 1: The attacker leverages Shellshock vulnerability in the lighttpd web server on Host 1 to penetrate into Host 1 from the attacker host. (2) Stage 2: The attacker discovers all the reachable hosts of Host 1 and connects to the discovered one, Host 2, using ssh. (3) Stage 3: The attacker uses tar to pack the sensitive files (e.g., /etc/passwd, /etc/shadow) on Host 2 as sensitive_data.tar. (4) Stage 4: The attacker uses scp on Host 1 to fetch the data sensitive_data.tar from Host 2. The attacker then uses curl on Host 1 to send the sensitive data back to the attacker host. We can observe that attack investigation faces a significant challenge of finding “a needle in a haystack”: a small number of critical attack-relevant edges (20; colored in dark black) are buried in an overwhelmingly large number (154K) of irrelevant edges. The same imbalance observation holds for attack-relevant nodes (20 vs. 101K).

3 SYSTEM OVERVIEW

Fig. 2 illustrates the architecture of RAPTOR. RAPTOR uses monitoring agents deployed on hosts to collect system audit logs. RAPTOR then parses the logs into a sequence of system events among system entities and sends the parsed data to the database for storage. Upon the database, RAPTOR provides a DSL, ProvQL, for investigating attack behaviors. ProvQL uniquely integrates a collection of constructs for attack pattern search and attack dependency tracking analyses, as well as constructs for iteratively refining intermediate investigation results. Given a ProvQL query input by the security analyst, the language parser performs syntax analysis and semantic analysis of it. The execution scheduler then generates an execution plan based on our specialized optimizations and schedules query execution. The error reporter reports errors during query execution. To allow users to easily construct ProvQL queries and inspect query results, RAPTOR provides a Jupyter Notebook-like UI with code cells (see our demo video [22]). Users can specify search queries, tracking queries, and other operations in code cells, and execute the cells to display the resulting graphs. Users can also retain the executed cells to document their investigation process.

Our threat model is similar to that of many previous works on system auditing [32, 37–40, 43, 44]. We assume the presence of an attacker seeking to attack the system from outside: the attacker may seek to access or modify unauthorized resources, exfiltrate confidential data, or install and spread malware. Our trusted computing base includes OS kernels, host agents, data storage, and the query execution engine. We assume that OS kernels and collected audit logs are secure from compromise. We do not consider malicious administrators who can disable the host agent or tamper
with system audit logs, or implicit information flows like covert and timing channels which do not go through kernel-layer auditing.

4 SYSTEM AUDITING INFRASTRUCTURE

Data model and monitoring agents. System auditing collects system-level events about system calls from the OS kernel. These events describe the interactions among various system entities. As shown in previous studies [34, 36, 37, 43, 44], on mainstream OSes, system entities are primarily files, processes, and network sockets, and system calls are mapped to three major types of system events: (1) file access, (2) processes creation and destruction, and (3) network access. Thus, in our data model, we primarily consider these system entities. We consider a system event as the interaction between two system entities represented as \((\text{subject_entity}, \text{operation_type}, \text{object_entity})\). Subject entities are processes from software applications (e.g., Chrome, Firefox) and objects can be files, processes, and network sockets. We categorize system events into three types according to the types of their object entities: file events, process events, and network events.

We develop monitoring agents using system auditing frameworks for different OSes: Sysdig [14] for Linux, Procmon [11] for Windows. Deployed on each host, our agent continuously monitors system activities, collects system audit logs, and extracts attributes critical for security analysis. Tables I and II show representative entity and event attributes that our agent extracts (e.g., file name, process executable name, IP address, event type). Following previous works [32, 34, 43], to uniquely identify entities, for a process entity, we use the process executable name and PID as its identifier. For a file entity, we use the absolute path as its identifier. For a network socket entity, we use the 5-tuple (source/destination IP, source/destination port, protocol) as its identifier. Failing to distinguish entities will cause problems in relating system events to entities and tracking dependencies among events.

Data storage. RAPTOR stores the parsed system entities and system events in the databases so that the collected provenance data can be persisted. The current implementation of RAPTOR supports two types of data storage backends: relational database PostgreSQL [25] and graph database Neo4j [23]. This enables RAPTOR to leverage the services these mature infrastructures provide, such as data management, indexing mechanism, querying, and data recovery. For PostgreSQL, RAPTOR stores system entities and system events in separate tables (six tables in total) with table columns for attributes. For Neo4j, RAPTOR stores system entities as nodes and system events as edges. Entities can be related to events by matching the entity ID with the subject/object ID attributes of events. Indexes are created on key attributes (e.g., file name, process executable name, source/destination IP) to speed up the search.

5 PROVQL LANGUAGE DESIGN

RAPTOR introduces a DSL, ProvQL, which uniquely integrates a set of constructs designed to express a wide range of queries for attack pattern search and attack causal dependency tracking. Grammar 1 presents the grammar. In Section 5.4, we demonstrate a series of ProvQL queries designed to uncover the data leakage attack illustrated in Fig. 1.

5.1 Multi-Step Attack Pattern Search

The search syntax (i.e., Rule \((\text{search} \_\text{stmt})\) in Grammar 1) allows users to specify multiple events with constraints, such as those on entity and event attributes or event relationships. This enables security analysts to search for multi-event patterns that represent complex, multi-step attack behaviors.

Take Query 1 in Section 5.4 as an example. First, we specify a database (e.g., 

\(\text{db(host1)}\)) as the data source of the search. Next, we define three system entities with constraints on their types and attributes (e.g., \(e1\text{[name="curl", type=process]}\)). Then, we define two system events using the three entities (e.g., \(e2[\text{read}]\rightarrow e1\), where the arrow indicates information flow direction) based on Rule \((\text{search} \_\text{rel} \_\text{expr})\). Besides the \textit{structural relationship} that two events are connected by the same entity \(e1\), we constrain their \textit{temporal relationship}: the two events occur within one second (e.g., \&\&[\text{<1s}] ). Together, these three entities and two events define a subgraph pattern depicting the attack behavior: using curl to transfer a sensitive tar file to an IP. The transfer is carried out by first reading data from the file and then writing the data to the socket.

After defining the multi-event pattern, we bind the results to a variable (e.g., \(\text{poi1}\)), indicating the results are maintained in memory. This variable can be used in subsequent queries (e.g., results of Query 1 are used as start entities for tracking in Query 2) for further refinement. We can also return the results and display the results in our UI.

5.2 Attack Causal Dependency Tracking

The tracking syntax (i.e., Rule \((\text{track} \_\text{stmt})\)) provides constructs for various types of fine-grained control of the causal dependency tracking process, including: tracking direction (backward/forward), POI, tracking depth, and entity and event constraints. This enables security analysts to effectively reduce the dependency explosion...
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The execution results of Query 5.3 Intermediate Results Binding produce a backward dependency graph, which is stored in the variable g2 for display in the UI and can be used in subsequent queries.

5.3 Intermediate Results Binding

ProVQL queries return a subgraph of events as results. Search queries return a subgraph that matches the specified multi-event pattern, while tracking queries return a subgraph aligned with the dependency tracking constraints. ProVQL is designed to help security analysts iteratively refine their investigation results. It allows them to bind query results to variables and maintain the results in memory, enabling analysts to access and modify the results through subsequent queries without reprocessing the entire dataset. This approach significantly reduces query execution time. For example, Query ➊ defines the variable g2 and binds it to the subgraph from the tracking process. Query ➋ then uses g2 as the data source for its search, i.e., search operates on the in-memory g2 rather than retrieving data from the database again.

To enable flexible manipulation of intermediate results, ProVQL supports various graph operations between variables. For instance, in Query ➊, a union operation (g2 | g3) merges the previously identified segments of the attack sequence, with the resulting subgraph bound to g4. Operations such as graph intersection and difference are also supported.

5.4 Example Queries for Investigating Multi-Step Attacks

We present a series of ProVQL queries that we constructed to uncover the data leakage attack depicted in Fig. 1. The investigation results (attack-relevant nodes and edges), after executing all queries, are highlighted in dark black in Fig. 1.

- **Query ➊**: We search for a malicious pattern on Host 1, where a sensitive tar file is transferred to an unknown IP. The results are bound to an in-memory variable poi.

```sql
1. select * from db(host1) where
2. e1(name="curl", type=process), e2(name="*tar", type=file), e3(type=network)
3. with e2(read)--e1 &<&1s> e1[write]--e3
4. return as poi;
```

- **Query ➋**: We investigate the origin of the tar file by tracing the backward dependencies of poi. To reduce the graph size, we exclude benign entities like vscode and limit the tracking depth. This backtracking reveals that the scp process is responsible for creating the tar file. The resulting graph is then bound to the variable g2 for further analysis.

```sql
1. g2 = backtrack poi1 from db(host1)
2. exclude nodes where name like "vscode"
3. limit step 2;
4. display g2;
```

- **Query ➌**: We search for related events of the process scp within the graph g2 and discover that scp reads from the socket on Host 2, confirming the origin.

```sql
1. select * from g2 where
2. e1(name="scp", type=process), e2(type=network),
3. e3(name="sensitive_data.tar")
4. with e2(read)-->e1 &<&10ms> e1[write]--e3
5. return *;
```

- **Query ➍**: Next, we investigate the attack's entry point on Host 1 by tracing the backward dependencies of the malicious curl process. Non-critical processes, such as ping, are filtered out. The tracking results are bound to g3.
A straightforward approach to executing a ProvQL query is to translate it into a semantically equivalent SQL or Cypher query for execution on the corresponding database. We can translate a ProvQL search query into a SQL or Cypher query that uses multiple joins and constraints, and we can translate a ProvQL tracking query into a SQL query using the recursive WITH clause or into a Cypher query using the path matching clause. However, as our evaluation results (Section 7.4) demonstrate, such execution scheduling is very inefficient when working with massive provenance data. This is because general-purpose query languages like SQL and Cypher are not optimized for system provenance data and cannot exploit the potential of domain-specific characteristics. For instance, the search task requires finding a multi-step attack pattern. This results in complicated SQL and Cypher queries with many joins and constraints, slowing down the performance. Similarly, the tracking task involves tracing the information flow recursively. This results in recursive SQL queries that need full table scans and many joins, or Cypher queries that match all potential paths first and then filter them by constraints (Cypher does not support on-the-fly constrained tracking [24]; see Section 7.4), which are both inefficient.

Efficient query scheduler. Raptor employs optimizations in its query scheduler to execute ProvQL queries efficiently. Instead of translating the entire ProvQL query into a large SQL or Cypher query and relying on the domain-agnostic scheduler provided by the DBMS, our idea is to break down the ProvQL query into smaller data retrieval steps according to its semantics, and translate each step into a small SQL or Cypher data query. Then, we can schedule the execution of these data queries in a domain-aware way.

Our scheduling algorithm optimizes the execution of data queries by considering their estimated pruning power, semantics, and dependencies. For a ProvQL search query, each event pattern (e.g., `e2[read]->e1`, `e1[write]->e3` in Query ① are two event patterns) is compiled into a small SQL or Cypher data query. The SQL query joins two entity tables and one event table, with constraints in the WHERE clause. Similarly, the Cypher query matches two entity nodes and one event edge with constraints. For each event pattern, Raptor computes a pruning score based on the number of constraints and the event type. A higher score indicates that the pattern can narrow the search space and yield fewer results. Event patterns with more constraints receive higher scores. Additionally, previous studies [52] show that file events are more frequent than network and process events on enterprise hosts. Thus, Raptor assigns lower scores to file event patterns. When scheduling data queries, Raptor considers both the pruning scores and event dependencies. If two event patterns are dependent (e.g., connected by the same entity), Raptor prioritizes executing the data query with the higher pruning score. The results from this data query are then used to further constrain the other data query (by adding additional WHERE clause conditions), reducing the search space. This approach ensures the efficient execution of complex, multi-event search queries.

For a ProvQL tracking query, we follow the dependency tracking procedure and decompose it into individual dependency retrieval steps. For each event popped from the queue, Raptor retrieves all causally dependent events by compiling the causal dependency conditions into small, non-recursive SQL or Cypher queries. In addition to the typical dependency conditions, such as information flow and time stamps, constraints on entities and events are also compiled into filters in the SQL or Cypher WHERE clause. Raptor executes these data queries sequentially, following the order in which events are popped from the queue, to retrieve all relevant dependencies. This approach enables Raptor to perform efficient, on-the-fly, constrained dependency tracking.

### 6 PROVQL EXECUTION ENGINE

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### 7 EVALUATION

We aim to answer several key research questions on defensive effectiveness, attack coverage, system efficiency, and DSL conciseness, through extensive evaluations.

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```sql
g3 = backtrack where exename like "curl" from db(host)
  include nodes where not path like "ping"
  limit time 5 min;
  display g3

Query ①: We search for the attack’s entry point within g3. Given that the attacker is likely operating from a remote server using the same IP (i.e., 20.69.152.188 as revealed in Query ①), we search for this IP in g3, which uncovers the lighttpd process. This process is then bound to poi2.

```
We constructed a comprehensive benchmark of 26 attack cases from four sources: (1) 8 multi-step intrusive attacks based on the Cyber Kill Chain Framework [5] and CVE [3] (for both Linux and Windows hosts; with prefix "multistep"); (2) 10 attacks based on commonly used exploits in previous studies [34, 43] (for Linux hosts; with prefix "malicious"); (3) 5 malware samples selected from Virus-Sign (for Windows hosts; with prefix "malware"); (4) 3 cases from the DARPA TC dataset [17] (with prefix "tc"). We collected system audit logs from our hosts with monitoring agents (one Windows and eight Linux hosts). We performed 23 cases ourselves, except for the DARPA TC cases, which used a public dataset (DARPA TC Engagement 5 Data Release [17]). The deployed server and hosts are frequently used by over ten active users to perform various daily tasks, including file manipulation, text editing, and software deployment. When we perform the attacks and conduct the evaluations, the server and hosts continue 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.

Table III lists all 26 attack cases, covering various operating systems, vulnerabilities (e.g., Firefox backdoor, shellshock), and exploits (e.g., Drakon APT). Due to space limitations, detailed descriptions of each case are available on our project website [26]. The system audit logs used in our evaluations contain a total of 1, 100, 584 system entities and 56, 454, 141 system events. Column “Original Prov. Graph” in Table IV shows the number of entities and events for each case, while Column “Attack Ground Truth” lists the number of malicious entities and events. The number of benign entities and events can be calculated by subtracting the values in Column “Attack Ground Truth” from those in Column “Original Prov. Graph”.

### 7.2 RQ1: Reducing Dependency Explosion

We evaluate the effectiveness of Raptor in reducing dependency explosion by measuring how much the dependency graphs can be reduced with fine-grained control provided by ProvQL. We compare Raptor with one seminal dependency tracking approach (BackTracker [37]) and two state-of-the-art approaches (PrioTracker [43] and DepImpact [32]) aiming to mitigate dependency explosion. BackTracker reconstructs the sequence of events leading to the POI events by analyzing event dependencies. PrioTracker improves over BackTracker by prioritizing abnormal dependencies during tracking. PrioTracker computes the priority of an event by its rarity and topological features in the dependency graph. DepImpact identifies critical components of a dependency graph (produced by BackTracker) that contain attack sequences. It assigns a dependency weight to each edge using features such as data flow relevance and temporal relevance. It then propagates the dependency impact score from the POI event to entry nodes based on edge weights. Following this, forward tracking is performed from the top-ranked entry nodes according to their scores. Critical components are then identified by taking the overlap of the backward and forward dependency graphs.

Raptor uses BackTracker as the underlying tracking algorithm for executing tracking queries. Since PrioTracker and DepImpact are not open-sourced, we implemented them ourselves. Following their papers, we set the time limit of PrioTracker to 180 seconds. For DepImpact, we select the top two entry nodes for small cases and the top five entry nodes for large cases. We confirmed with the authors of PrioTracker and DepImpact that our implementations and settings are correct.

Inspired by DepImpact, we designed a five-step investigation pipeline for Raptor: (1) labeling POI events based on detection alerts; (2) performing backward tracking from POI events; (3) identifying suspicious entry nodes; (4) performing forward tracking from the suspicious entry nodes; (5) identifying attack sequences...
We compare different approaches in revealing attack sequences. Here, F is the proportion of irrelevant events included. F1-score is calculated using three metrics adopted from previous works [32]: miss rate ($M_R$), noise ratio ($N_R$), and Cypher query, which specify the

Table IV: Sizes of output graphs generated by RAPTOR (i.e., with ProvQL queries) and prior approaches. RAPTOR achieves the highest graph reduction rate and outperforms existing approaches by a significant margin.

| Case                          | Raptor | BackTracker | PrioTracker | DepImpact | ProvQL | Attack Ground Truth | Original Prov. Graph |
|-------------------------------|--------|-------------|-------------|-----------|--------|--------------------|----------------------|
| multistep_cmd_injection      | 10     | 12          | 13          | 13        | 10     | 11                 | 7.45                 |
| multistep_data_leakage       | 8      | 14          | 10          | 10        | 8      | 7.3                | 7.3                  |
| multistep_netcat_backdoor    | 2      | 5           | 14          | 14        | 2      | 2.9                | 2.9                  |
| multistep_password_track     | 11     | 13          | 18          | 18        | 11     | 12.8               | 12.8                 |
| multistep_penetration        | 36     | 52          | 27          | 27        | 36     | 7.3                | 7.3                  |
| multistep_phishing_email     | 5      | 5           | 7           | 7         | 5      | 5                  | 5.4                  |
| multistep_suppression        | 7      | 37          | 4           | 4         | 7      | 4                  | 5.4                  |
| multistep_warranty           | 31     | 115         | 30          | 30        | 31     | 12.8               | 12.8                 |
| malicious_weget              | 16     | 39          | 10          | 10        | 16     | 12.8               | 12.8                 |
| maliciousIllegal_store       | 10     | 18          | 22          | 22        | 10     | 12.8               | 12.8                 |
| malicious_hide_file          | 6      | 10          | 11          | 11        | 6      | 12.8               | 12.8                 |
| malicious_backdoor_all       | 11     | 20          | 20          | 20        | 11     | 12.8               | 12.8                 |
| malicious_server_use         | 106    | 209         | 11          | 11        | 106    | 12.8               | 12.8                 |
| malicious_ssh_stealth        | 5      | 8           | 14          | 14        | 5      | 12.8               | 12.8                 |
| malicious_grr_crash          | 10     | 18          | 18          | 18        | 10     | 12.8               | 12.8                 |
| malicious_scan_login          | 17     | 13           | 4           | 4         | 17     | 4                  | 4                  |
| malicious_password_reuse     | 7      | 11          | 11          | 11        | 7      | 12.8               | 12.8                 |
| malicious_student            | 19     | 30          | 30          | 30        | 19     | 12.8               | 12.8                 |
| malware_autores              | 8      | 21          | 11          | 11        | 8      | 12.8               | 12.8                 |
| malware_danger               | 4      | 12          | 12          | 12        | 4      | 12.8               | 12.8                 |
| malware_hijack               | 7      | 14          | 14          | 14        | 7      | 12.8               | 12.8                 |
| malware_infector             | 5      | 11          | 11          | 11        | 5      | 12.8               | 12.8                 |
| malware_rux                  | 8      | 10          | 10          | 10        | 8      | 12.8               | 12.8                 |
| tc_fiveDirections_1           | 8      | 17          | 17          | 17        | 8      | 12.8               | 12.8                 |
| tc_fiveDirections_2           | 11     | 21          | 21          | 21        | 11     | 12.8               | 12.8                 |
| tc_theis                     | 3      | 6           | 6           | 6         | 3      | 12.8               | 12.8                 |
| Total                        | 375    | 957         | 589980.7x   | 589980.7x | 375    | 589980.7x          | 589980.7x             |

We calculate the graph reduction rate (GR) [32], defined as the ratio of edges in the original graph to those in the graph resulting from the investigation. As shown in Table IV: (1) RAPTOR achieves the highest GR of 58, 991x, while BackTracker, PrioTracker, and DepImpact have GR values of 9x, 42x, and 24x, respectively. (2) The sizes of the graphs generated by RAPTOR are close to the attack ground truth. Compared to RAPTOR, BackTracker generates much larger graphs due to its lack of control. PrioTracker performs better than BackTracker in large TC cases due to its prioritization of events. For small cases, the graph generated by PrioTracker is the same as BackTracker, while the tracking can be finished within the time limit. However, it is hard to determine a proper time limit in different scenarios. DepImpact reduces graph size through intersection and outperforms BackTracker. However, a key limitation is that DepImpact, like BackTracker and PrioTracker, is a fixed algorithm with limited user customization. DepImpact’s performance depends heavily on the selection of entry nodes, but determining the optimal number of nodes for different cases is challenging. Too few may result in missing critical information, while too many can introduce irrelevant information. These design limitations and lack of flexibility hinder DepImpact’s performance.

7.3 RQ2: Revealing Attack Sequences

We compare different approaches in revealing attack sequences using three metrics adopted from previous works [32]: miss rate ($M_R$), noise ratio ($N_R$), and F1-score. Miss rate, defined as $MR = FN/E_{total}$, measures the proportion of attack-relevant events that are not identified. Noise ratio, defined as $NR = FP/E_{total}$, measures the proportion of irrelevant events included. F1-score is calculated as $F1 = (TP + 0.5 \times (FP + FN))/(TP + FP + FN)$, balancing precision and recall. Here, $TP$ refers to true positives. $FP$ is the number of irrelevant events (identified false positives). $ FN$ is the number of missed attack-relevant events. $E_{total}$ is the total number of attack-relevant events. $E_{total}$ is the total number of events.

As shown in Table V, RAPTOR outperforms existing approaches significantly, with a higher $F1$, and lower $MR$ and $NR$, indicating that RAPTOR can effectively reveal the attack sequence while removing irrelevant events. Compared to RAPTOR, BackTracker has a higher $NR$ due to the dependency explosion, which causes huge graphs. BackTracker also has a higher $MR$ because events occurring after the POI event are excluded from backward tracking. PrioTracker has higher $NR$ and $MR$ than RAPTOR. For large TC cases, although PrioTracker generates smaller graphs than BackTracker, the graphs are still very large (with $N_R$ approaching 1). For other cases, PrioTracker generates the same graphs as BackTracker (explained in Section 7.2). RAPTOR also outperforms DepImpact on both $MR$ and $NR$ thanks to ProvQL’s customization. Note the performance of DepImpact depends on the selection of entry nodes. However, determining the optimal number of entry nodes for different cases is challenging (e.g., in multistep_penetration, many initial access trials are missed by DepImpact, resulting in a high $MR$).

In malicious_weget, RAPTOR’s forward tracking reveals attack sequences not shown in the backward dependency graph from the POI event, presenting a more complete attack result (resulting in a higher $MR$ but a lower $NR$). In malicious_pwd_reuse, we use ProvQL queries to exclude node $x_z$, which has many irrelevant events (resulting in a higher $MR$ but a lower $NR$).

7.4 RQ3: ProvQL’s Execution Efficiency

We evaluate the runtime performance of RAPTOR with and without our two optimizations: query scheduling and in-memory management. We create a benchmark dataset for this RQ from the ProvQL queries used in RQ1 and RQ2, where each case has a backward tracking query, a search query, and a forward tracking query. For each ProvQL search query, we construct a semantically equivalent SQL query (using CROSS JOIN) and Cypher query, which specify the

through graph intersection. Each step is performed with ProvQL search or tracking queries, with constraints to filter out irrelevant events. We follow this pipeline to construct queries to investigate each attack scenario. The queries are available at [27].
Table V: F1-Score, Miss Rate (MR), and Noise Ratio (NR) for Raptor, BackTracker, PrioTracker, and DepImpact. Raptor outperforms all three approaches significantly with a much higher F1, and much lower MR and NR.

| Case                      | F1-Score  | MR     | F1-Score  | MR     | F1-Score  | MR     | F1-Score  | MR     | F1-Score  | MR     |
|---------------------------|-----------|--------|-----------|--------|-----------|--------|-----------|--------|-----------|--------|
| multistep_cmd_injection   | 0.7143    | 0      | 0.4444    | 0.3509 | 0         | 0.7872 | 0         | 0.3509 | 0         | 0.7872 |
| multistep_data_leakage    | 0.6286    | 0.0762 | 0.2143    | 0.2681 | 0.381     | 0.8289 | 0.2661    | 0.381  | 0.8289    | 0.2922 |
| multistep_netcat_backdoor | 0.5714    | 0.3333 | 0.5       | 0.0012 | 0.3333    | 0.9994 | 0.0012    | 0.3333 | 0.9994    | 0.0424 |
| multistep_password_crack  | 0.8695    | 0.2308 | 0.1459    | 0.9213 | 0.1459    | 0.9213 | 0.1818    | 0      | 0.9       |
| multistep_penetration     | 0.9052    | 0.1731 | 0.1818    | 0.8837 | 0.5833    | 0.1818 | 0.8837    | 0.5833 | 0.12      | 0.9302 |
| multistep_plishing_email  | 0.9375    | 0.1176 | 0.0504    | 0.9773 | 0.0854    | 0.9773 | 0.0008    | 0.9773 | 0.0018    | 0.7556 |
| multistep_supplychain     | 0.9901    | 0.1667 | 0.25      | 0.6667 | 0.25      | 0.8    | 0.6467    | 0.25   | 0.6        | 0.6279 |
| multistep_wannacry        | 0.8557    | 0.2522 | 0.195     | 0.593  | 0.195     | 0.593  | 0.99      | 0.0249 | 0.6421    | 0.9871 |
| malicious_weft            | 0.5715    | 0.0588 | 0.5897    | 0.5641 | 0.3529    | 0.5    | 0.5641    | 0.3529 | 0.5       | 0.5406 |
| maliciousIllegal_store    | 0.8859    | 0.1111 | 0.1111    | 0.5926 | 0.1111    | 0.5556 | 0.5926    | 0.1111 | 0.5556    | 0.2    |
| malicious_hide_file       | 1         | 0      | 0         | 0.8889 | 0.2       | 0     | 0.8889    | 0.2    | 0         | 0.7144 |
| malicious_backdoor_dl     | 0.8889    | 0      | 0.2       | 0.4445 | 0.25      | 0.6842 | 0.4445    | 0.25   | 0.6842    | 0.6667 |
| malicious_server_usr      | 0.9952    | 0.0095 | 0         | 0.9881 | 0.0142    | 0.0995 | 0.9881    | 0.0142 | 0.0895    | 0.8564 |
| malicious_ssh_theft       | 0.8571    | 0      | 0.25      | 0.6    | 0         | 0.5714 | 0.6       | 0      | 0.5714    | 0.6    |
| malicious_gcc_crash       | 0.875     | 0      | 0.2222    | 0.875  | 0         | 0.2222 | 0.875     | 0      | 0.2222    | 0.4444 |
| maliciousScan_login       | 1         | 0      | 0         | 1.263  | 0         | 0.9326 | 0.1263    | 0      | 0.9326    | 0.6251 |
| malicious_pw_duse         | 0.7407    | 0.375  | 0.0909    | 0.0444 | 0.25      | 0.9771 | 0.0444    | 0.25   | 0.9771    | 0.32    |
| malicious_student         | 0.8824    | 0      | 0.2105    | 0.2037 | 0.2667    | 0.8817 | 0.2037    | 0.2667 | 0.8817    | 0.7097 |
| malwareAutoRun           | 0.8649    | 0      | 0.2381    | 0.01   | 0         | 0.995  | 0.01      | 0      | 0.995     | 0.0036 |
| malware_danger           | 1         | 0      | 0         | 0.0004 | 0         | 0.9998 | 0.0004    | 0      | 0.9998    | 0      |
| malware_hijack           | 1         | 0      | 0         | 0.0004 | 0         | 0.9998 | 0.0004    | 0      | 0.9998    | 0      |
| malware_infect          | 0.9524    | 0      | 0.0099    | 0.0024 | 0         | 0.9988 | 0.0024    | 0      | 0.9988    | 0      |
| malware_sysbot           | 1         | 0      | 0         | 0.0026 | 0         | 0.9987 | 0.0026    | 0      | 0.9987    | 0      |
| tcFiveDirections_1       | 0         | 0      | 0         | 1      | 0         | 0      | 1         | 0      | 0         | 0      |
| tcFiveDirections_2       | 0.8842    | 0      | 0.2075    | 0.0002 | 0.3869    | 0.9999 | 0.0004    | 0.3659 | 0.0000    | 0.9978 |
| tcTheia                  | 1         | 0      | 0         | 0      | 0         | 1      | 0         | 0      | 1         | 0      |

Average: 0.8766 0.0525 0.1858 0.2526 0.1855 0.7731 0.2526 0.1855 0.7731 0.2604 0.3999 0.6578
Table VI: Execution time (in milliseconds) for RAPTOR, RAPTOR-DB, and SQL/Cypher for search and tracking analyses. Each query is executed for 10 rounds. The time-out threshold is 30 minutes. We exclude DARPA TC cases (marked with "-") from the Neo4j database evaluation due to their time-out in data loading. ProvQL queries are more efficient than SQL and Cypher queries for search and tracking, thanks to RAPTOR’s query scheduler and in-memory management mechanism.

| Case                  | PostgreSQL | Neo4j | PostgreSQL | Neo4j | PostgreSQL | Neo4j | PostgreSQL | Neo4j | PostgreSQL | Neo4j |
|-----------------------|------------|-------|------------|-------|------------|-------|------------|-------|------------|-------|
| multistep_cmd_injection | 71         | 83    | 907        | -     | 3,512      | 3,762 | 3,700      | -     | 3,512      | 3,762 |
| multistep_data_leakage | 115        | 139   | 1,093      | 2,761 | 3,836      | 5,542 | 2          | 12    | 26         | 32    |
| multistep_netcat_backdoor | 283     | 239   | 1,177      | 3,586 | 3,675      | 25,165 | -1         | 12    | 15         | 1     |
| multistep_password_crack | 109      | 141   | 895        | 2,361 | 3,100      | 5,817 | -1         | 12    | 10         | 1     |
| multistep_penetration   | 181        | 175   | 1,335      | 6,459 | 8,020      | 186,311 | -1         | 7     | 11         | 1     |
| multistep_phishing_email | 503     | 512   | 4,115      | 5,377 | 8,414      | Time-out | 1         | 21    | 32         | 1     |
| multistep_suppchain    | 36         | 47    | 856        | 11,130 | 1,335      | 3,702 | 1         | 8     | 9          | 1     |
| multistep_wannacry     | 197        | 242   | 554        | 2,727 | 3,694      | 79,245 | -1         | 12    | 11         | 1     |
| malicious_wget         | 44         | 77    | 1,076      | 1,293 | 1,697      | 7,508 | -1         | 9     | 12         | -1    |
| malicious_illegal_store | 40       | 55    | 902        | 1,392 | 1,762      | 7,050 | -1         | 10    | 10         | 1     |
| malicious_hide_file    | 38         | 43    | 1,051      | 1,275 | 1,422      | 7,520 | 1          | 11    | 13         | -1    |
| malicious_backdoor_dll | 51         | 63    | 1,082      | 1,628 | 1,967      | 7,900 | -1         | 9     | 14         | -1    |
| malicious_server_usr   | 38         | 43    | 940        | 1,569 | 1,799      | 26,187 | 1         | 10    | 11         | -1    |
| malicious_ssh_theft    | 30         | 43    | 879        | 1,344 | 1,750      | 2,770 | -1         | 9     | 11         | -1    |
| malicious_gcc_crash    | 46         | 59    | 875        | 1,601 | 1,949      | 4,925 | -1         | 8     | 11         | -1    |
| malicious_scan_login   | 54         | 96    | 924        | 1,786 | 2,222      | 800,991 | -1        | 8     | 13         | 1     |
| malicious_pwd_reuse    | 48         | 58    | 918        | 1,472 | 1,567      | 58,673 | -1        | 11    | 11         | -1    |
| malicious_student      | 63         | 83    | 58         | 1,456 | 1,763      | 1,870 | -1         | 9     | 13         | -1    |
| malware_autorun       | 216        | 262   | 2,270      | 2,463 | 3,320      | 30,271 | -1        | 14    | 18         | 1     |
| malware_danger        | 1,601      | 2,007 | 104,999    | 19,679 | 30,499     | Time-out | 8         | 62    | 67         | 9     |
| malware_hijack        | 670        | 682   | 61,264     | 8,600 | 10,390     | 1,447,395 | 1        | 34    | 40         | 1     |
| malware_infector      | 397        | 482   | 6,122      | 3,803 | 4,356      | 456,675 | 7        | 61    | 66         | 4     |
| malware_symbot        | 385        | 443   | 3,678      | 3,481 | 4,107      | 472,575 | 11        | 52    | 73         | 7     |
| tc_fivedirections_1   | 2,739      | 3,105 | 67,386     | -     | -          | -     | 1         | 12    | 16         | -     |
| tc_fivedirections_2   | 65,664     | 68,841 | 7,401     | -     | -          | -     | 19        | 3,438 | 3,576      | -     |
| tc_theia             | 133        | 178   | 22,480     | -     | -          | -     | 1         | 12    | 13         | -     |
| Average              | 2,837      | 3,007 | 11,355     | 3,425 | 4,544      | 192,383 | 2        | 149   | 158        | 1     |

This is because directly manipulating in-memory results is much faster than retrieving data from the database.

With our query scheduling and in-memory management optimizations together, RAPTOR achieves an overall speedup of 4.06× over SQL and 56.18× over Cypher.

7.5 RUQ: Usability Study and Query Concreteness

We conducted a user study to evaluate RAPTOR’s usability and ease of adoption. The study was designed to compare ProvQL with SQL, the most widely used query language, to validate its efficiency, learning curve, and practicality in attack investigation tasks. Although Cypher and Splunk were initially considered, we excluded them due to the lack of participants with experience in these languages.

We recruited 10 participants with SQL experience and security background. Each participant was asked to complete a set of investigation tasks using SQL and ProvQL. To ensure a fair comparison, we divided the tasks into two categories based on complexity. Simple tasks involve attacks targeting a single host and require fewer queries to investigate. Complex tasks involve complex, multi-host attacks that require more investigative queries. We ensured that the selected cases were of similar difficulty within each category. Ultimately, we chose malicious_ssh_theft and malicious_illegal_store for the simple category, and multistep_supply_chain and multistep_penetration for the complex category (listed in Table III).

To control for potential learning effects, where participants may perform better in later tasks due to familiarity, we alternated the language used for each case. For example, a participant would solve one malicious case using SQL and the other using ProvQL. Following this approach, each participant would complete four initial tasks: malicious_ssh_theft with SQL, malicious_illegal_store with ProvQL, multistep_supply_chain with SQL, and multistep_penetration with ProvQL. Additionally, we wanted to assess how easily users transition from one language to another especially when analyzing complex attacks. Thus, we designed an opposite-language assessment: for each complex case, participants would solve it a second time using the alternative language. We focused exclusively on complex cases because they showcase ProvQL’s advantages in simplifying intricate investigations by handling much of the heavy lifting for users. In simple cases, these advantages are less evident and might amplify the learning effect. Conversely, in complex cases, the structural differences between SQL and ProvQL still require users to adapt. This approach allows us to meaningfully assess whether ProvQL’s high-level constructs ease the query process and reduce cognitive load, enabling users to focus more directly on the investigation. Therefore, each participant would complete two additional transition assessment tasks: multistep_supply_chain with ProvQL and multistep_penetration with SQL.

Each participant signed a consent form with an approved IRB number. They were provided with a PostgreSQL database containing provenance data along with the schema description. They also received a description of each case and specific investigation goals. Example goals included identifying the attacker’s IP address and the process IDs (PIDs) of key processes involved in the attack. Identifying these indicators confirmed the successful completion of the investigation. A time limit of 30 minutes was allocated for each simple case, while complex cases had a 45-minute limit.

The study began with a brief tutorial covering the syntax and functionality of ProvQL. Participants were then guided through a sample investigation using both PostgreSQL and SQL on a tutorial case.
malicious wget. Participants were provided with sample SQL and ProvQL queries for this tutorial case, which they could reference as needed during investigations. They also had access to the ProvQL’s grammar and were allowed to search SQL syntax online. Each participant completed the study individually, using our laptop with the environment setup. Participants used Raptor’s UI [22] for ProvQL investigations and pgAdmin for SQL investigations.

To document the investigation process, each participant’s screen activity was recorded (without microphone or camera), while ensuring no sensitive data was collected. We analyzed the recorded screen sessions to measure the time taken and the number of queries taken to complete each task. After completing all tasks, participants completed a QuestionPro survey to provide feedback, rating each query language on ease of use, syntax simplicity, and overall user experience. The survey used a 5-point Likert scale to assess key aspects such as query complexity, language intuitiveness, and participants’ preferences between SQL and ProvQL.

**User study results.** We present our study results. For the simple cases, the malicious_ssh_theft task was completed using SQL in an average of 19 minutes, requiring approximately 3 queries. The malicious_illegal_store task, when solved with ProvQL, was completed in 7 minutes, with an average of 1.7 queries. For the complex cases, the multistep_supply_chain demonstrated improved efficiency with ProvQL, taking 4 minutes compared to 6 minutes with SQL, and requiring fewer queries on average (2.2 vs. 3.0). The most significant difference was observed in the multistep_penetration case, where ProvQL users completed the task in 16 minutes with 3 queries, while only 33% of SQL users completed the task within the 45-minute timeout, requiring an average of 30 minutes and 5.6 queries. The results indicate that, although SQL users benefited from their familiarity with the syntax, the verbosity of SQL led to increased completion times and query counts. In contrast, ProvQL’s specialized features enabled more efficient investigation workflows.

We also analyzed user feedback from the survey. The detailed survey questions and results are available on our project website [26]. Four key metrics were assessed: ease of query writing, result interpretation, event search, and tracking event sequences. Participants rated each metric on a 5-point scale (Very Complex, Complex, Neutral, Easy, and Very Easy) to evaluate the usability of ProvQL and SQL. ProvQL consistently received higher ratings, with most participants finding it “Easy” or “Very Easy” across all metrics. Specifically, 100% rated ProvQL as “Easy” or better for event searching, and 70% found it “Very Easy” for tracking sequences. SQL, however, received mixed responses, with many participants rating it as “Complex” or “Very Complex” across all metrics. Additionally, 100% of participants found ProvQL easier to work with than SQL. For the transition between languages, 90% of participants rated the switch from SQL to ProvQL as “Easy” and 10% as “Very Easy”. However, the reverse transition (from ProvQL to SQL) proved more challenging, with 70% rating it as “Complex” and 20% as “Very Complex”.

These findings confirm that ProvQL offers significant usability advantages. Participants reported that ProvQL’s simplified syntax and intuitive constructs made query writing easier and complex event searches more efficient. The transition from SQL to ProvQL was largely seamless, with most users adapting quickly and rating ProvQL as easy to use, even as a new language. In contrast, SQL presented greater challenges, especially when analyzing complex attacks. Overall, the user study findings underscore ProvQL’s significant usability advantages to streamline investigative workflows, reduce cognitive load, and enhance the user experience.

7.5.1 **Query Conciseness.** We further compare the conciseness of ProvQL with SQL, Cypher, and an industry security DSL, Splunk SPL. Splunk [28], a widely used security log analysis solution, employs its own DSL, Splunk SPL, for investigating system logs. However, Splunk SPL lacks native support for recursive queries that are essential for tracking [13]. Thus, we limit our comparison to search queries for Splunk SPL. We reuse the queries from RQ3 and additionally construct semantically equivalent Splunk SPL queries for each case. We then count the number of words and characters in each query.

Detailed results are available on our project website [26], along with example queries in these languages. ProvQL tracking queries are more concise than SQL and Cypher. On average, tracking queries in ProvQL contain 19 words, compared to 421 words in SQL and 183 words in Cypher. While Cypher is more concise than SQL due to its direct modeling of graph structure, it becomes verbose when using multiple FOREACH loops to traverse nodes and edges. ProvQL is also more concise than other languages in search queries. On average, search queries in ProvQL contain 15 words, compared to 192 in SQL, 25 in Cypher, and 62 in Splunk SPL. The verbosity in SQL and Splunk SPL stems from the need to use multiple joins to express relationships between entities, which becomes cumbersome with complex constraints and multiple joins. Cypher, while explicitly modeling node relationships, requires MATCH statements to define patterns and WHERE clauses to specify constraints, resulting in lengthy queries when expressing complex relationships.

8 **DISCUSSION AND FUTURE WORK**

**Raptor** enables the integration of human expert feedback through its carefully designed DSL. Analysts can seamlessly switch between search queries, tracking queries, and result binding operations to iteratively refine their investigation. Using the search syntax, analysts can define patterns for entities, how entities connect to form events, how events link to build a graph, with various constraints on entity and event attributes, event temporal ordering and structural relationships, etc. Similarly, in tracking queries, analysts can impose constraints on nodes and edges to mitigate dependency explosion, control tracking directions, and define conditions for when to stop tracking. Support for iterative investigation is achieved through three key design elements: (1) Analysts can refine individual queries by modifying constraints or adding/removing entities and events; (2) They can use result binding operators to pass results between queries; (3) Query execution is fast through our scheduling algorithm and in-memory mode.

One limitation of all query tools is the need for analysts to manually construct queries. Nevertheless, Raptor streamlines this process through its intuitive, expressive DSL and efficient execution engine. As demonstrated by our evaluation results and usability study, Raptor is much more effective and user-friendly for attack investigations than other query alternatives.
A promising direction for future research is to automate the query construction process. One approach is to leverage the extensive external threat knowledge offered by cyber threat intelligence (CTI). According to Gartner [45], CTI provides evidence-based knowledge about threat behaviors, which is critical for organizations to monitor the rapidly evolving threat landscape and uncover sophisticated cyber-espionage campaigns. Notably, a large number of publicly available CTI reports, such as security blog articles [12, 20] and security news [21], provide valuable insights into threat behaviors within their textual descriptions. These reports contain a wide range of entities, including Indicators of Compromise (IOCs) (e.g., names of malicious files and processes, IP addresses of botnets), vulnerabilities, threat actors, attack tactics and techniques, as well as the relations among these entities.

Several studies have attempted to extract knowledge entities and relations from CTI reports to construct cybersecurity knowledge graphs [29, 41, 48], including our previous work [33], aiming to build a comprehensive threat profile. However, effectively leveraging CTI knowledge to enhance downstream defenses remains an important yet underexplored challenge. Thus, future work can explore ways to enable automated, CTI-enhanced attack investigation. For example, we can leverage the CTI knowledge to synthesize or suggest ProvQL queries, potentially conditioned on the current investigation status and investigation history, drawing on techniques from neural program synthesis [51] and code suggestion [42]. Analysts can further edit the synthesized queries to incorporate additional insights and refine the investigation process.

9 RELATED WORK

Provenance-based attack investigation. To mitigate dependency explosion in causal dependency tracking, recent efforts proposed prioritizing dependencies using heuristic rules [32, 34, 43], which can result in information loss. For example, PrioTracker [43] assigns a higher priority score to processes with fewer dependencies. However, this approach may overlook attacks that exploit complex software (e.g., web browsers) with extensive dependencies (e.g., reading and writing many files). Other approaches aim to improve tracking granularity by partitioning process execution into smaller units [39, 44], which require program instrumentation and kernel changes, limiting their adoption. Unlike RAPTOR, they do not offer users fine-grained control over the tracking process.

Another category of approaches detects attack behaviors within provenance graphs through subgraph matching. Given a query graph, these methods identify aligned subgraphs within the provenance graph. Poirot [46], a non-learning-based approach, applies heuristic rules to search for node alignments, selects aligned nodes for graph traversal, and chooses the best graph alignment from the traversal results. However, as reported in later works [30, 50], Poirot’s heuristics (e.g., its path-scoring function) require traversing large portions of the graph, resulting in significant computational overhead when the query and provenance graphs are large. Also, since Poirot stops the search after finding the first acceptable alignment, it may miss key nodes and edges in other alignments. In contrast, learning-based approaches, such as ProvG-Searcher [30] and DeepHunter [50], use graph neural networks to learn graph embeddings to determine subgraph relationships. ProvG-Searcher uses GraphSAGE, while DeepHunter uses neural tensor networks. However, these methods can only determine whether a query graph is entailed within the provenance graph, without finding the exact aligned subgraph that depicts specific attack steps. Moreover, the embedding models must be trained offline in advance (which is costly) and often struggle with generalization in dynamic enterprise environments where system behaviors frequently change.

RAPTOR’s scope differs from all these works. Rather than developing another subgraph matching algorithm, RAPTOR introduces a DSL alongside an efficient execution engine. The key advantage lies in facilitating user knowledge incorporation and iterative investigation. In these subgraph matching works, the exact form of the “query graph” is not clearly defined, which impacts the ease and flexibility with which users can incorporate knowledge and make updates. In contrast, RAPTOR formalizes this process through its DSL. Unlike Poirot, RAPTOR goes beyond finding the best match, identifying all subgraphs that align with the ProvQL query. Unlike ProvG-Searcher and DeepHunter, RAPTOR requires no offline model training, and its online query execution is optimized for efficiency. Furthermore, these subgraph matching works do not support dependency tracking queries covered by RAPTOR.

Log analysis tools and query languages. Splunk [28] and Elasticsearch [7] are among the most widely used log analysis tools for performance monitoring and security diagnostics. Splunk offers a search processing language (SPL) with keyword and regex-based searches and shell-like piping to extract insights from logs. Elasticsearch provides a JSON-based DSL for text search and filtering. OSQuery [10] is an open-source tool that uses a SQL-like syntax to query the state of operating systems. Unlike RAPTOR (ProvQL), these languages lack support for complex dependency tracking queries, which are critical for tracing attack event chains. Regarding other general-purpose query languages, SPARQL [49] is designed to query data stored in RDF format, with syntax similar to SQL. MongoDB [31] is a document-oriented database with a JSON-like query language. However, like SQL and Cypher, these languages are not optimized for the system provenance domain. Their syntax is low-level and verbose, and their execution is not optimized for iterative attack investigation.

10 CONCLUSION

RAPTOR is a system that enables human-in-the-loop investigation of complex attacks through an expressive and efficient domain-specific language, ProvQL. Future work involves integrating external security knowledge from cyber threat intelligence to further automate the attack investigation process through techniques such as query synthesis and suggestion.

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