ThreatKG: A Threat Knowledge Graph for Automated Open-Source Cyber Threat Intelligence Gathering and Management

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***Abstract*—Despite the increased adoption of open-source cyber threat intelligence (OSCTI) for acquiring knowledge about cyber threats, little effort has been made to harvest knowledge from a large number of unstructured OSCTI reports available in the wild (e.g., security articles, threat reports). These reports provide comprehensive threat knowledge in a variety of entities (e.g., IOCs, threat actors, TTPs) and relations, which, however, are hard to gather due to diverse report formats, large report quantities, and complex structures and nuances in the natural language report text.**

To bridge the gap, we propose ThreatKG, a system for automated open-source cyber threat knowledge gathering and management. ThreatKG automatically collects a large number of OSCTI reports from various sources, extracts high-fidelity threat knowledge, constructs a threat knowledge graph, and updates the knowledge graph by continuously ingesting new knowledge. To address multiple challenges, ThreatKG provides: (1) a hierarchical ontology for modeling a variety of threat knowledge entities and relations; (2) an accurate deep learning-based pipeline for threat knowledge extraction; (3) a scalable and extensible system architecture for threat knowledge graph construction, persistence, updating, and exploration. Evaluations on a large number of reports demonstrate the effectiveness of ThreatKG in threat knowledge gathering and management.

I. Introduction

Sophisticated cyber attacks have plagued many high-profile businesses [1]–[3]. To remain aware of the fast-evolving cyber threat landscape and gain insights into the most dangerous threats, security researchers and practitioners actively gather knowledge about cyber threats from past incidents, and share the knowledge through public sources like security websites and blogs. Such open-source cyber threat intelligence (OSCTI) [4] has received growing attention from the community.

Despite the pressing need for high-quality threat knowledge to empower defenses, existing OSCTI gathering and management systems [5]–[12], however, have primarily focused on structured Indicator of Compromise (IOC) feeds [13], which are forensic artifacts of intrusions such as hashes of malware samples, names of malicious files/processes, and IP addresses of botnets. Though useful in capturing fragmented views of threats, these IOCs are low-level and disconnected, and thus they lack the capability to uncover the complete threat scenario as to how the threat unfolds into multiple steps, which is typically observed in most sophisticated attacks these days [14]. Consequently, defensive measures that rely on these low-level, fragmented indicators are easy to bypass when the attacker re-purposes the tools and changes their signatures [4].

In contrast, a large number of unstructured OSCTI reports have been significantly overlooked (e.g., security blogs and news [15]–[21], threat encyclopedia pages [22], [23]), which contain more comprehensive knowledge about threats in natural language text. Besides low-level IOC entities, OSCTI reports contain various (1) *higher-level threat knowledge entities* (e.g., threat actors, adversary tactics, techniques, and procedures (TTPs) [24]), and (2) *semantic relationships* between entities that indicate their interactions (e.g., the launch relation between two IOCs Office Monkeys (Short Flash Movie).exe and player.exe in Figure 2b). Such high-level and connected knowledge is tied to the attacker's goals and thus more difficult to change, which is critical for uncovering the complete multi-step threat scenario and building more robust defenses [25]. As the volume of OSCTI reports increases day-by-day, it becomes increasingly challenging for threat analysts to manually maneuver through and correlate the myriad of sources to gain useful knowledge. Unfortunately, prior approaches do not provide an automated and principled way to gather such knowledge from OSCTI reports and manage the knowledge.

Challenges. In this work, we seek to design and build a system that (1) automatically gathers high-fidelity cyber threat knowledge from a large number of OSCTI reports, and (2) manages such knowledge in a unified knowledge base to provide comprehensive views of various threats. We identify four major challenges. First, in addition to IOCs, OSCTI reports contain various other types of entities and relations that capture threat behaviors. To comprehensively model the threats, the system needs to have a wide coverage of entity and relation types. Second, OSCTI reports collected from different sources have diverse formats: some reports contain structured fields such as tables/lists, and some reports primarily contain natural language text (e.g., Figure 2). Besides, not all reports from a source capture threat behaviors (e.g., advertisements, product promotions [13]). Thus, the system needs to handle such diversity and filter out irrelevant reports. Third, accurately extracting threat knowledge from natural language text is

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non-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 limit the performance of most natural language processing (NLP) modules (e.g., sentence segmentation, tokenization), making existing information extraction tools ineffective [26], [27]. Besides, learning-based information extraction approaches typically require a large annotated training corpus, which is expensive to obtain manually. Thus, how to programmatically obtain annotations becomes another challenge. Fourth, new OSCTI reports are being published every day that contain fresh knowledge about the latest threats. Being able to provide threat knowledge timely will facilitate downstream defensive measures in effectively countering these threats. Thus, the system needs to continuously gather new knowledge and integrate it to update the knowledge base. The system also needs to be scalable (to handle the large report volume) and extensible (to generalize to new reports with unseen formats).

Contributions. We propose THREATKG (∼26K LOC), a system for automated open-source cyber threat knowledge gathering and management. THREATKG automatically collects a large number of OSCTI reports from a wide range of sources, uses a combination of ML and NLP techniques to extract high-fidelity threat knowledge, constructs a *threat knowledge graph*, and updates the knowledge graph by continuously ingesting new knowledge. To address the aforementioned challenges, THREATKG has the following key designs:

(1) *Hierarchical Threat Knowledge Ontology:* To comprehensively model the threats, THREATKG employs a hierarchical ontology, which consists of three layers that model the threats in different dimensions and granularities. The ontology covers a wide range of low-level and high-level entities (i.e., IOCs, threat actors, malware, TTPs), the relations of which depict both low-level detailed threat behavior steps and high-level threat contexts. Compared to other cyber ontologies that only focus on sub-domains of threat behaviors (e.g., malware behavior [28], [29]) and cover a limited set of entities and relations (e.g., lacking TTPs and IOC relations [30], [31]), THREATKG's ontology is much more comprehensive in its threat knowledge coverage (Section III-B).

(2) *Deep Natural Language Understanding for Threat Knowledge Extraction:* To generalize well to diverse OSCTI report formats, THREATKG decouples the threat knowledge extraction pipeline into different processing components: parsers, checkers, and extractors. Parsers are source-dependent: each parser handles the specific layout structure of each OSCTI source and parses the collected report files into unified threat knowledge representations (UTKRs), which contain the parsed structured fields (e.g., report title, author, publisher) and unstructured text blocks. Checkers then operate on these UTKRs and filter out non-threat reports using ML-based techniques (Section III-C). Extractors are source-independent: they perform an in-depth analysis of unstructured text, and extract a variety of entities and relations to further enrich the UTKRs. By decoupling the processing, THREATKG can easily generalize to new OSCTI report formats (via adding parsers) and new entity/relation types (via adding extractors).

To accurately extract threat knowledge from unstructured OSCTI text, an in-depth natural language understanding is critical. THREATKG employs a specialized NLP pipeline that targets the unique problem of extracting a variety of entities and relations from OSCTI text, which has not been studied in prior work. To deeply understand the complex logical structures of OSCTI text and the semantic meaning and connections between targeted entities, THREATKG employs a collection of rule-based and deep learning (DL)-based techniques (e.g., IOC protection, dependency parsing, neural named entity recognition and neural relation extraction) in its extractors to handle the nuances and achieve accurate threat knowledge extraction (Sections III-D1 and III-D2). In addition, to obtain a large annotated corpus for training DL models, we leverage data programming [32] to programmatically synthesize annotations for targeted entities and relations in text (Section III-D3).

(3) *Scalable and Extensible System Architecture:* To gather and provide threat knowledge timely, THREATKG employs a scalable and extensible system architecture that manages all components for OSCTI report collection, threat knowledge extraction, threat knowledge graph construction, persistence, and updating. The architecture employs a modular design, allowing multiple components in the same processing step to share the same interface and produce outputs together. Such modular design allows THREATKG to parallelize and pipeline the execution of the processing components to improve the throughput. Existing components can be switched off and new components can be easily added via a configuration file (e.g., adding new crawlers and parsers for a new OSCTI source), making THREATKG extensible. THREATKG is fully automated: new reports are being collected and the extracted knowledge is being continuously integrated into the knowledge graph. Upon the threat knowledge graph, various downstream security applications can be empowered. In particular, THREATKG provides a GUI that provides various types of interactivity to facilitate threat search and threat knowledge graph exploration (Sections III-E and III-F).

Deployment and Evaluation. We deployed THREATKG on a lab server and evaluated its effectiveness thoroughly. At the time of writing, THREATKG has collected 149K+ OSCTI reports from 40+ sources. The constructed threat knowledge graph contains 347K+ entities and 1.73M+ relations.

Our evaluation results demonstrate that: (1) THREATKG is able to accurately filter out non-threat reports and extract various types of threat knowledge from OSCTI text, and can generalize to unseen OSCTI sources; (2) Compared to existing security information extraction approaches, THREATKG has a much wider coverage of threat knowledge types and is more accurate; (3) the entire pipeline of THREATKG is efficient (able to finish the expected daily workload in < 30s).

To the best of our knowledge, THREATKG is *the first system that automatically constructs a large knowledge graph for cyber threats from OSCTI reports*. A system demo video is available at [33].

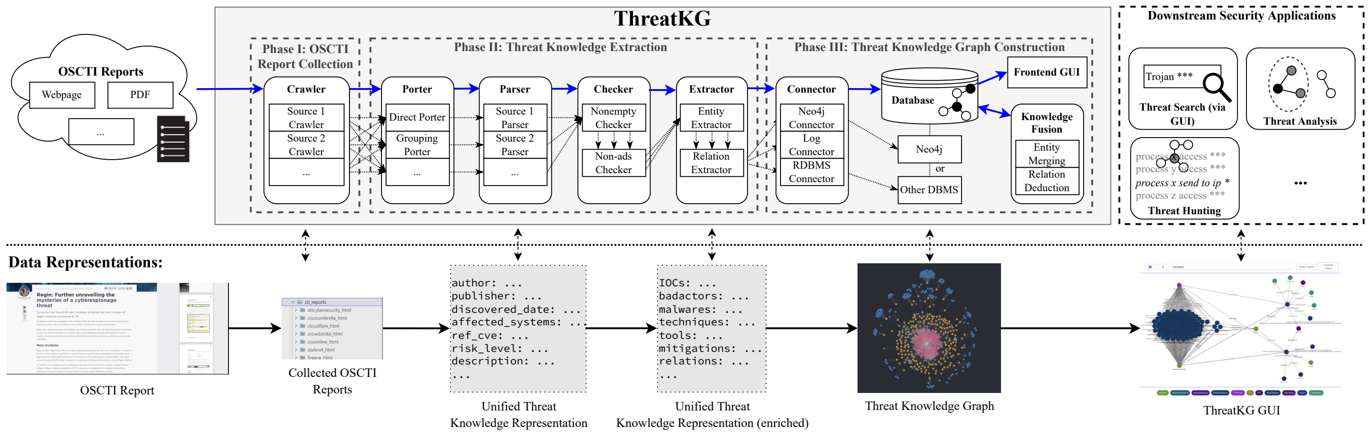


Fig. 1: The architecture of THREATKG. Arrows between system components represent data flows.

II. SYSTEM OVERVIEW

Figure 1 shows the architecture of THREATKG, which consists of three phases: (1) OSCTI report collection, (2) threat knowledge extraction, and (3) threat knowledge graph construction. Each phase consists of one or several processing steps (e.g., Parser, Extractor). In Phase I, THREATKG collects OSCTI reports from a wide range of sources (Crawler). In Phase II, THREATKG groups multi-page report files (Porter), parses the reports (Parser), filters out non-threat reports (Checker), and extracts threat knowledge (Extractor). In Phase III, THREATKG constructs a threat knowledge graph and persist it in the database. THREATKG is automated and continuously running, with new reports being periodically and incrementally collected and new knowledge being extracted and integrated into the knowledge graph via knowledge fusion.

Motivating Example. We show two representative OSCTI reports to motivate the design. Figure 2a shows a report snippet from Trend Micro threat encyclopedia [34] about the Ransom.Win32.LOCKBIT.YEBGW ransomware. The report is semi-structured; it contains a few structured fields about certain attributes of the malware (e.g., aliases, platform), as well as unstructured text about the detailed behaviors of the malware (e.g., dropping a file). Figure 2b shows a report snippet from Securelist blog [35] about the Office Monkeys dropper used by the CozyDuke threat actor. The complete report is about the CozyDuke threat actor, which primarily contains unstructured text on its contexts and behaviors.

We can observe that OSCTI reports have diverse formats. Besides, the unstructured text contains rich knowledge about threat behaviors. We annotated representative entities and relations in both reports. We can observe that some entity-relation triplets indicate detailed threat behavior steps (e.g., <Office Monkeys (Short Flash Movie).exe, launch, player.exe>). Besides, information about the sequential order of some steps maybe be presented (e.g., "...first...then..." in Figure 2b). In addition to detailed threat behavior steps, we can also observe that some triplets provide high-level threat contexts, in which the relations may not be explicitly associated with words in text (e.g., the CozyDuke actor uses the Office Monkeys (Short Flash Movie).exe dropper file to perform the attack). To uncover the complete multi-step threat scenario, the approach needs to accurately extract these triplets from text, infer the possible order of some triplets, and resolve entity coreferences (e.g., arrows in the figures) to connect the triplets.

Significance of THREATKG. Various downstream security applications can be empowered by the constructed threat knowledge graph. To facilitate threat analysts in acquiring knowledge about desired threats, THREATKG provides a GUI for threat search and interactive threat knowledge graph exploration. Intrusion detection systems [36] can integrate the gathered threat knowledge as the signature of an intrusion, making these systems able to counter the latest threats. Cyber threat hunting systems [37] can also leverage the gathered knowledge to guide the threat hunting process. In Section V, we discuss THREATKG's usefulness and applicability in detail.

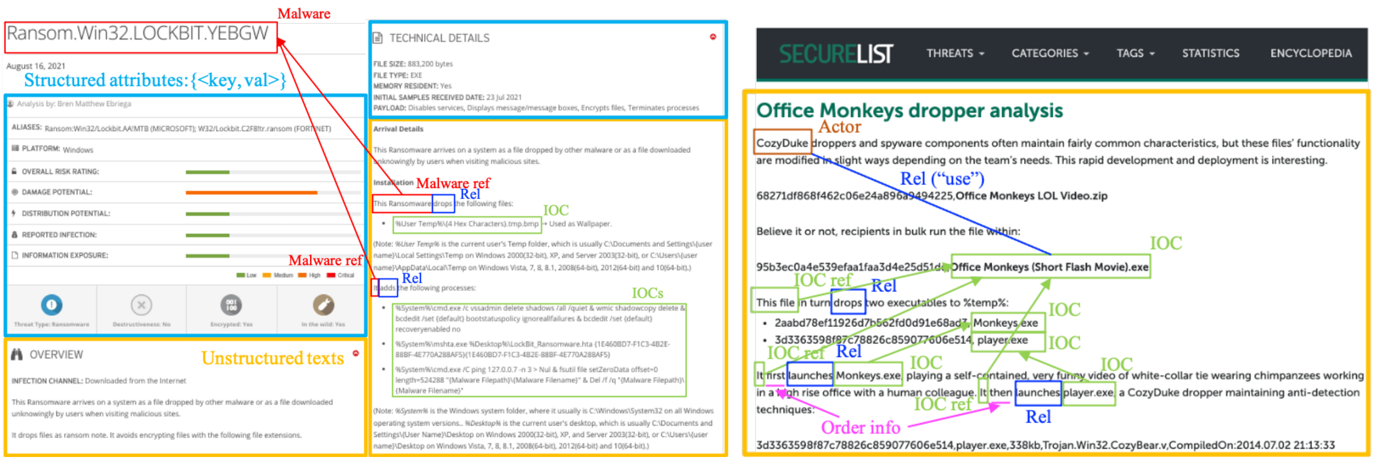
Different from existing knowledge graphs [38]–[43] designed for storing and representing general knowledge, such as person names and organizations, THREATKG automatically constructs a knowledge graph from a large number of OSCTI reports for cybersecurity domain, with the goal of empowering a wide range of downstream security applications. THREATKG releases threat analysts from intensive and tedious manual threat knowledge gathering process, enabling them to redirect energy to other more important defensive tasks.

III. DESIGN OF THREATKG

In this section, we present the design details of THREATKG.

A. OSCTI Report Collection

We built a robust multi-threaded crawler framework that manages crawlers to collect OSCTI reports from 40 major security websites, including: threat encyclopedias [22], [23], enterprise security blogs [15]–[17], influential personal security blogs [18], [19], security news [20], [21], etc. These websites provide a large number of OSCTI reports (in the form of webpages) that cover various types of threats (e.g., malware, vulnerabilities, attack campaigns), making them a valuable source of threat knowledge. Each crawler handles the specific layout structure of each website and is able to handle both static pages and dynamically generated content (e.g., the "View More" button in [15]) to collect individual report URLs.



(a) (b)

Fig. 2: Example OSCTI reports that contain rich threat knowledge. (a) Semi-structured report snippet from Trend Micro threat encyclopedia. The report [34] is about the ransomware, `Ransom.Win32.LOCKBIT.YEBGW`. (b) Unstructured report snippet from Securelist. The report [35] is about the `CozyDuke` actor and the snippet is about its dropper file.

The crawler framework schedules periodic execution and reboot after failure for individual crawlers in a robust manner. To boost the crawling efficiency, the crawler framework employs a multi-threaded design that schedules parallel execution for multiple crawlers, as well as fetching multiple reports for each crawler. With THREATKG's extensible system architecture, new OSCTI sources can be easily added by adding a corresponding crawler and a corresponding parser.

To further expand the threat knowledge coverage, in addition to the 40 security websites, we collected OSCTI reports from another useful source, APTnotes [44]. APTnotes is a repository of publicly-available reports related to malicious campaigns/activities/software that have been associated with vendor-defined APT groups. These reports are in PDF format and are typically longer than the collected webpages, which provide complementary threat knowledge. We used the script provided in [44] and downloaded 542 reports in total.

B. Hierarchical Threat Knowledge Ontology

Based on our observations of a wide range of OSCTI sources, we categorize OSCTI reports into three broad types: malware reports, vulnerability reports, and attack reports. Malware reports and vulnerability reports are semi-structured reports collected from threat encyclopedias [22], [23], which contain knowledge about malware or vulnerabilities. Figure 2a shows an example malware report snippet on the Ransom.Win32.LOCKBIT.YEBGW ransomware. Attack reports are unstructured reports collected from security blogs and news [15]–[21], which contain knowledge about attack campaigns. Figure 2b shows an example attack report snippet on the CozyDuke APT attack (CozyDuke is the name of the threat actor/group that is responsible for the attack).

To comprehensively model the threats, we construct a hierarchical threat knowledge ontology that includes a variety of threat knowledge entities and relations for capturing both low-level threat behaviors and high-level threat contexts. Figure 3 shows the ontology, which consists of three layers. The report context layer of the ontology contains report-level knowledge. Specifically, for each report, we associate it with an entity of the corresponding type. This entity has attributes like title, URL, publication date, etc. Having explicit entities for reports would help threat analysts connect other threat knowledge entities (e.g., malware, IOCs, TTPs) gathered from the same report to form a comprehensive view of the threat. Threat analysts can also view the original report by following the URL attribute to obtain more context. Besides, reports are written by specific authors and created by specific CTI vendors, for which we create entities as well. These entities and their relations form the report context layer.

The threat behavior layer of the ontology contains knowledge on low-level threat behaviors. As shown in prior research [37], [45], IOCs and their relations contain important knowledge on how the threat unfolds into low-level connected steps. Such knowledge can be used to identify system call events (e.g., process reading a file) that are part of the attack sequence, which would largely benefit defensive measures like cyber threat hunting. For example, in Figure 2b, two filename IOCs, Office Monkeys (Short Flash Movie).exe and player.exe, have a launch relation. Thus, in the threat behavior layer, we consider different types of IOCs and their relations. Example IOC types are filename, filepath, IP, URL, domain, registry, and hashes. We follow the prior research [37], [45] and consider the interaction verbs (e.g., read, write, open, send) between the IOCs as their relations.

The threat context layer of the ontology provides high-level contexts for threats in addition to detailed threat behavior steps. Such contexts are critical to a comprehensive understanding of threats and designing effective countermeasures accordingly. For this layer, we consider a wide range of entities, including: (1) malware (e.g., BlackEnergy trojan [46]), (2) vulnerabilities (e.g., CVEs [47]), (3) threat actors (e.g., CozyDuke APT actor [35]), (4) tactics and techniques (e.g., spearphishing link [24]), (5) vulnera-

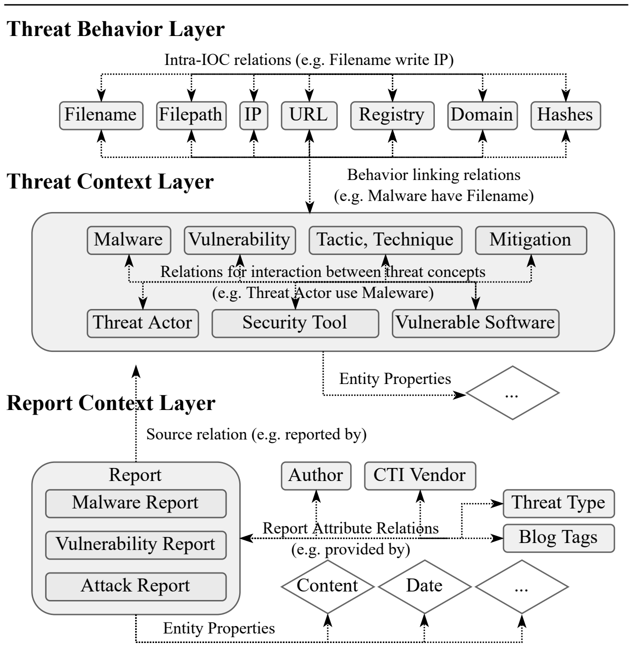


Fig. 3: Hierarchical threat knowledge ontology

ble software products (e.g., Microsoft Word), (6) security-related tools (e.g., Mimikatz [48]), (7) mitigations (e.g., data backup [24]), and (8) relevanters (e.g., infected computers). These entities can have various types of relations between them. Let's use TYPE_ENT to denote an entity placeholder of the type "TYPE". Example entity-relation triplets in this layer are <ACTOR_ENT, use, MALWARE_ENT> and <SOFTWARE_ENT, has, VULNERABILITY_ENT>.

Entities in different layers can also be related. For example, entities in the threat behavior layer and the threat context layer that are gathered from the same report are related to the corresponding report entity (in the report context layer) through a reported_in relation. In Figure 2a, the malware entity Ransom.Win32.LOCKBIT.YEBGW is related to several filepath IOC entities through an add relation (after coreference resolution). In Figure 2b, the threat actor entity CozyDuke is related to the filename IOC entity Office Monkeys (Short Flash Movie).exe through a use relation. Entities can also have attributes in the form of key-value pairs (e.g., type of a malware, version of a vulnerable software). The three layers of ontology collectively model the threats from multiple dimensions and in different granularities. Compared to other cyber ontologies [28]–[31], THREATKG's ontology has a much wider coverage of threat knowledge types, enabling threat analysts to obtain a more comprehensive view of threats.

C. OSCTI Report Parsing and Threat Relevance Checking

Once the crawlers collect the OSCTI reports, the porters group multi-page report files. The parsers are source-dependent; each parser parses the specific layout structure of the corresponding OSCTI source and converts the report files into unified threat knowledge representations (UTKRs). UTKR is a JSON schema that covers relevant and potentially useful information in OSCTI data sources and lists out corresponding fields. We construct this schema by iterating through OSCTI data sources and adding fields for previously undefined types of knowledge. Figure 1 shows an example schema, which contains fields such as title, author, and publication date. Specifically, the parsers first convert the reports into UTKRs (i.e., Python objects in memory) by parsing the structured fields. Unstructured text blocks are also parsed and put into UTKRs. Then, the extractors further enrich the UTKRs by extracting additional entities and relations from unstructured text and putting them into the corresponding fields.

The UTKR is different from the ontology described in Section III-B. The ontology conceptually specifies what types of knowledge we target and how the knowledge is structured, which is used to guide the threat knowledge graph construction. In contrast, the UTKR specifies the actual form of OSCTI data that resides in the system and is passed between system components. As we will discuss in Section III-E, having a unified intermediate representation that all components (parsers, checkers, extractors) can work on will largely increase system modularity and promote scalability and extensibility.

Threat Relevance Checking. As the crawlers simply collect the report files by following the URLs and do not have visibility into the report content, there could be reports collected that do not contribute valuable knowledge to modeling cyber threats (e.g., empty pages, ads, product promotions, irrelevant news [13]). Keeping these reports in the knowledge extraction pipeline will waste computation resources for the extractors and impair the quality of the gathered threat knowledge. Therefore, THREATKG employs a set of checkers that operate on the UTKRs produced by the parsers and filter out reports that are irrelevant to cyber threats. The filtered UTKRs are then passed to the extractors for further enrichment.

Empty web pages can be easily filtered out using simple rules. Hence, we construct a rule-based checker for these reports. For ads and other irrelevant reports, we model the checking process as a binary classification task and construct learning-based checkers: given an OSCTI report, determine whether or not it is relevant to cyber threats.

To train the classifier, we extract a set of useful features, including: (1) *Keyword count & density in the report title and body:* We obtain a list of keywords from MITRE ATT&CK [24] for example threat actors, malware, tools, techniques, etc.; (2) *IOC count & density in the report body:* We extract IOCs using regex rules (see Section III-D1). We don't consider report title as most of the titles do not contain threat details like IOCs; (3) *Report article length:* Based on our observations, a longer report is more likely to contain threat behaviors (e.g., list of IOCs in Figure 2a); (4) *TF-IDF values for tokens:* We prioritize the frequent, unique tokens by calculating the TF-IDF [49] value for each token in the report. We use these features to train a variety of ML models (e.g., SVM, Random Forest, XGBoost, LightGBM) and evaluate their performance on our ground-truth dataset. The experimental results and analysis are in Section IV-B1.

D. Threat Knowledge Extraction

The extractors take the UTKRs produced by the parsers as input, perform an in-depth natural language understanding of unstructured text, and extract a variety of entities and relations to further enrich the UTKRs. The extractors are source-independent: every extractor extracts the targeted threat knowledge from unstructured text universally for all OSCTI sources, and the extraction does not depend on the layout structure of each source. By decoupling the threat knowledge extraction process into source-dependent parsing and source-independent extraction, THREATKG can be easily extended to incorporate new OSCTI sources (via adding crawlers and parsers) and new knowledge types (via adding extractors).

1) Threat Knowledge Entity Extraction: For IOCs, we construct a set of regex rules that cover a wide range of IOC types (e.g., filename, filepath, IP, URL, domain, registry, hashes). THREATKG incorporates these rules in a rule-based entity extractor. For other types of entities (e.g., malware, threat actors, tools) that are hard to specify using rules, THREATKG employs a DL-based extractor to perform neural named entity recognition. Named entity recognition (NER) is a task of information extraction that seeks to locate and classify named entities mentioned in unstructured text into pre-defined categories [50]. Compared to conventional NER approaches like Hidden Markov Model [51], DL-based approaches avoid the time-consuming feature engineering stage and can better understand deep semantics of text and capture hidden patterns, leading to more accurate extraction.

Unique Challenges for Threat Knowledge Extraction. As mentioned in Section I, compared to general information extraction, we are faced with two unique challenges for extracting threat knowledge from OSCTI text. First, massive nuances exist in OSCTI text that are particular to the security context (e.g., dots, underscores, spaces, slashes in IOCs). These nuances confuse many basic NLP modules (e.g., sentence segmentation, tokenization) and hence the extraction techniques built upon these modules. Second, for general information extraction where the goal is to extract general entities (e.g., person names, organizations, locations) and relations, the community has already curated many benchmark datasets using sources like news corpus and Wikipedia (e.g., CoNLL-2003 [52] for named entity recognition, SemEval-2010 Task 8 [53] for relation extraction). However, there is no labeled dataset for the threat knowledge extraction task that covers wide range of entities and relations that we target. What's more, DL-based information extraction approaches typically require the annotated training corpus to be large, but it is expensive to annotate a large OSCTI corpus manually. These challenges apply to both the threat knowledge entity extraction task and the threat knowledge relation extraction task.

To address the first challenge, as these nuances mostly exist in IOCs, we leverage a method called IOC Protection proposed in our other work [37], by replacing IOCs with meaningful words in natural language context (e.g., the word "something") and restoring them after the tokenization procedure. This way, we guarantee that the potential entities are complete tokens. To address the second challenge, we leverage data programming [32] to programmatically synthesize annotations for targeted entities and relations in OSCTI text. We will discuss the details of data programming in Section III-D3.

Neural NER. We construct a Bidirectional LSTM-CRF (BiLSTM-CRF) model [54] to perform neural NER over OSCTI text. (1) First, each input sentence is tokenized and each token is transformed into an embedding vector via one-hot encoding. (2) Then, the embeddings are forwarded to the bidirectional LSTM (BiLSTM) layer, which consists of two LSTM networks that process the input sentence in the forward and backward directions. LSTM (Long-Short Term Memory) [55] is known for its capability in capturing long-term dependencies of tokens. However, a single LSTM can only remember information from the past context. For tasks like NER, understanding the context of a token through both past and future contexts is necessary. Thus, we add an additional LSTM to construct the BiLSTM layer, which processes the information in a bidirectional manner. The BiLSTM essentially acts like a deep feature extractor that captures the sequential relationships among the input tokens. (3) The outputs from the BiLSTM are forwarded to a linear layer, which maps the features extracted by the BiLSTM from the feature space into the tag space. After mapping, the outputs are forwarded to a Conditional Random Field (CRF) layer [56] which outputs optimal, joint prediction of all the tags in the sentence. During inference, each input token is propagated through the network and the Viterbi algorithm [57] is applied at the CRF layer to find the most optimal sequence for the output tags.

2) Threat Knowledge Relation Extraction: As mentioned in Section III-B, there exist relations that can be directly associated with interaction verbs between two entities (e.g., drop, add relations in Figure 2a; drop, launch relations in Figure 2b), as well as relations that may not be explicitly associated with words in text (e.g., the use relation between CozyDuke and Office Monkeys (Short Flash Movie).exe in Figure 2b). These relations (and the associated entities) capture both low-level threat behaviors and high-level threat contexts.

Dependency Parsing-Based RE. For the first type of relations, THREATKG employs a dependency parsing-based relation extractor to extract interaction verbs between two entities. In our other work [37], we proposed a light-weight, unsupervised NLP pipeline for extracting various verbs between two IOCs in OSCTI text, which has achieved high extraction accuracy. Our approach leverages dependency parsing to analyze the grammatical structure of a sentence and constructs a dependency tree, and then uses a set of dependency grammar rules to locate the subject-verb-object relations between IOCs to extract the targeted relation verb. Besides, our approach can also extract the sequential order of IOC interaction steps if presented, which is useful for understanding the threat scenario. Thus, in THREATKG, we leverage this approach to extract verbs between two IOCs. We further extend it to support the extraction of verbs between any types of entities listed in our ontology (e.g., drop, add relations between malware and IOCs in Figure 2a), by extending the IOC recognition step with our neural NER model.

It is important to note that compared to our other work [37], THREATKG has a completely different goal: THREATKG targets extracting a wide range of entities and relations from a large number of OSCTI reports to automatically construct a threat knowledge graph. In contrast, [37] targets extracting only IOCs and IOC relations from a single OSCTI report and using the extracted information for threat hunting.

Neural RE. For the second type of relations, as these relations are not associated with explicit verbs in text, the previous dependency parsing-based approach will not work. Thus, we model the relation extraction as a multi-class classification task: given a sentence that contains two entities recognized by our entity extractors, determine which relation category the sentence belongs to. Here, the entities include the IOCs recognized by our IOC rules and the other entities recognized by our BiLSTM-CRF model. Example relation categories include USE (i.e., use something to achieve a goal), CREATE (i.e., generate or make something that did not exist before), BREAK (i.e., stop or prevent something from happening), FIND (i.e., discover or locate something), ALIAS (i.e., two entities are synonyms). In general, two entities could have a relation when they co-occur within a certain distance. These entities could co-occur in the same sentence or in different sentences. In the current implementation of THREATKG, we focus on entities that co-occur in the same sentence, as these entities are most likely to generate high-quality relations based on our observations.

Specifically, THREATKG employs a DL-based relation extractor that leverages a Piecewise Convolutional Neural Networks model with attention mechanism (PCNN-ATT) to perform neural relation extraction (RE). The PCNN [58] model is similar to the Convolutional Neural Networks (CNN) model widely used for image and text classification tasks. However, PCNN is specially designed for relation extraction: Instead of using a single max pooling to merge features as in CNN, PCNN uses piecewise max pooling, which splits a sentence into three parts by the two entities and calculates the maximum value of each parts. Compared to CNN, PCNN is more suitable for relation extraction because the two entities in the sentence (and their locations) capture the structural information about the sentence and are critical for identifying the important tokens between them that indicate the relation. Moreover, since the tokens in a sentence are not equally helpful to relation extraction, an additional attention layer is added to make the model focus on tokens that are more important.

After the NER and before the RE, THREATKG performs coreference resolution [59] to find all expressions (e.g., pronouns) in the text that refer to a specific entity. Figure 2 shows example entity coreferences indicated by the arrows. This way, the RE can benefit from the information provided by the resolved entities and the extracted triplets can be connected to form a comprehensive view of threat knowledge.

3) Data Programming: To train DL-based models for NER and RE, a large annotated corpus is needed. However, manually annotating such corpus is expensive: for NER, we need to annotate each token in the text with a tag in the BIO format; for RE, we need to annotate each sentence in the text with a relation category as well as the types and location spans of the entities in the sentence. To mitigate the cost of obtaining supervision, we leverage data programming [32], which programmatically synthesizes annotations via unsupervised modeling of sources of weak supervision. Specifically, data programming first obtains the domain knowledge expressed by subject matter experts via labeling functions (could be noisy rules based on heuristics), and then denoises and integrates these sources of weak supervision to synthesize annotations.

We leverage an open-source realization of data programming, Snorkel [60], to programmatically build large training sets for our NER and RE tasks. The entire labeling pipeline of Snorkel is unsupervised (i.e., does not require labeled data for training): after we construct the labeling functions, Snorkel will automatically learn and assign weights for the labeling functions and produce a single set of noise-aware confidence-weighted labels for the input samples.

The key to synthesizing good annotations is to define noisy but helpful labeling functions. To synthesize annotations for the NER task, we create labeling functions based on our curated lists of entity keywords. For example, the list of threat actors, malware, techniques, and tools are constructed from MITRE ATT&CK [24]. To synthesize annotations for the RE task, we create labeling functions based on distant supervision and checking the entity types and keywords existence: (1) Distant supervision [61] is a technique that generates training data using an already existing knowledge base. The idea is that if there exists a fact between two targeted entities in the knowledge base, we can then label each pair of the targeted entities that appear in the same sentence as a positive example for the relation that the fact represents. This way, we can generate a large number of (noisy) labeled sentences. Specifically, in our setting, we leverage MITRE ATT&CK, which is a manually curated knowledge base for cyber adversary behaviors and its data is available in a downloadable structured JSON file. For example, for a sentence that contains one threat actor entity and one malware entity, if the two entities exist in the MITRE ATT&CK JSON and have the “use” relation type, we then label the sentence with the USE relation category. (2) We also construct labeling functions based on heuristic rules that check the entity types and the existence of keywords. For example, for the ALIAS relation, we check if the two entities have the same type and if there exist some keywords like “alias” or “aka”. By leveraging data programming, we can generate large amount of training data with relatively low human efforts.

E. Scalable and Extensible System Architecture

Threat Knowledge Graph Construction. After the extractors enrich the UTKRs, THREATKG constructs the threat knowledge graph from the UTKRs and stores it into the backend database for persistence. Directly inserting the UTKRs leads to inefficient storage. Furthermore, these long representations are not convenient for end users (e.g., threat analysts) to comprehend and analyze. Thus, THREATKG refactors these intermediate representations to match the threat knowledge ontology, which is separately designed and has clear and concise semantics for entities and relations. THREATKG then merges the refactored representations into the database through its connectors. Currently, THREATKG uses Neo4j [62] for its storage, with nodes being entities and edges being relations. Each node is associated with a category (e.g., malware or threat actor), a unique name (e.g., specific malware name), and a set of attributes. New databases backends can be easily supported by adding the corresponding connectors, thanks to the modular design of THREATKG's system architecture.

Scalability and Extensibility. To make the system scalable, we parallelize the system components for the processing steps (e.g., crawlers, parsers, checkers, extractors). We further pipeline the processing steps to improve the throughput of threat knowledge extraction. Between different processing steps, we specify the formats of intermediate representations (i.e., UTKRs) and make these representations serializable. These UTKRs are passed through the pipeline and get enriched. With such a pipeline design, we can have multiple computing instances for a single processing step and pass serialized intermediate results across the distributed network, making multi-host deployment and load balancing possible.

To make the system extensible, we adopt a modular design, allowing multiple system components in the same processing step to work together with the same input/output interface. For example, THREATKG has multiple crawlers to collect OSCTI reports from multiple sources, and THREATKG can import report data from the collected HTML files, PDF files, or compressed formats by using different types of porters. In addition, THREATKG provides rich configuration support: the system can be configured through a configuration file, which specifies the set of components to use and the additional parameters (e.g., threshold values for NER) that are passed to these components. With this design, existing components can be switched off and new components can be easily added.

Continuous Knowledge Integration. To provide the latest threat knowledge timely, THREATKG is fully automated and continuously running, with new reports being collected and new knowledge being extracted and integrated into the threat knowledge graph. At the time of writing, THREATKG has collected $149,015$ reports, and the threat knowledge graph has accumulated $347,243$ entities and $1,732,469$ relations.

When referring to the same entity, different sources may use different identifiers (e.g., "ZQuest" and "Z-Quest" refer to the same adware). To make the knowledge stored in the threat knowledge graph consistent, THREATKG aggregates knowledge from multiple sources via knowledge fusion. In knowledge fusion, THREATKG scans all the extracted entities and merges facts about the same entity by creating a new entity as the merged result and migrating all relations. One key challenge is that in the threat knowledge domain, entities with similar names might be completely different (e.g., "Petya" and "NotPetya" are two ransomware with names satisfying a substring relation but are different entities). To address this challenge, THREATKG takes the advantage of the contextual information stored along with the entity and only triggers merges when two candidate entities have similarity in its name (e.g., semantic similarity computed using word embeddings [63]) that surpasses a configurable threshold, have no conflicts in their attribute values, and operate in a similar environment (e.g., operating on the same platform). By considering the contextual information extracted along with the entity identifier and merging only when there is no conflict, THREATKG reduces the information loss in its knowledge fusion procedure, while providing a consistent and comprehensive view for entities mentioned in multiple sources.

F. Frontend Web GUI

To facilitate threat search and knowledge graph exploration, we built a web GUI using React and Elasticsearch. The GUI interacts with the Neo4j database and provides various types of interactivity. The user can zoom in/out, drag the canvas, click on a node and an edge to display the detailed information, and search information using keywords (through Elasticsearch) or Cypher queries (through Neo4j Cypher engine). Once the user drags a node, the GUI responds to the node movements to prevent overlap through an automatic graph layout using the Barnes-Hut algorithm [64]. The dragged nodes will lock in place but are still draggable if selected. This feature facilitates defining custom graph layouts for visualization. The GUI also supports convenient inter-graph navigation. When a node is double-clicked, if its neighboring nodes have not appeared in the view yet, these neighboring nodes will automatically spawn. On the contrary, once the user is done investigating a node, if its neighboring nodes or any downstream nodes are shown, double clicking on the node again will hide all its neighboring nodes and downstream nodes. In addition, the user can configure the number of nodes displayed and the maximum number of neighboring nodes displayed for a node, and view the previous graphs displayed.

Note that the Neo4j database also provides the Neo4j Browser for data exploration. Compared to it, our GUI is not tied to the specific database backend, and it is easy to switch to a different database (e.g., RDF store) while providing the same functionalities. Furthermore, unlike the Neo4j Browser that can only perform structured Cypher query search, our GUI also supports fuzzy keyword search powered by Elasticsearch, which is easier to use and facilitates quick exploration. Such design also opens up possibilities for building more types of threat analytics over the threat knowledge graph and integrating these anlaytics in the GUI (e.g., acquiring threat knowledge through natural language question answering).

IV. EVALUATION

We built THREATKG ($\sim$26K LOC) upon several tools: Python for the system, BeautifulSoup and Selenium for the

TABLE I: Statistics of ground-truth OSCTI dataset

Data Source	Category	# Reports
apt_notes	APTnotes	15
kaspersky_threat	Encyclopedia	45
symantec_threat	Encyclopedia	45
attcybersecurity	Enterprise Blog	12
crowdstrike	Enterprise Blog	6
securelist	Enterprise Blog	7
symantecthreatintelligence	Enterprise Blog	11
Total:		141

crawlers, scikit-learn and Ray Tune (for hyperparameter optimization) for the checkers, PyTorch for the extractors, Snorkel for data programming, and Neo4j for the storage backend.

We deployed THREATKG on a lab server and conducted extensive experiments to evaluate THREATKG's performance. We aim to answer the following research questions:

- **RQ1:** How accurate is THREATKG in filtering out OSCTI reports that are irrelevant to cyber threats?
- **RQ2:** How accurate is THREATKG in extracting threat knowledge entities and relations from OSCTI text? Does data programming help improve the performance?
- **RQ3:** How good is THREATKG in gathering various types of threat knowledge compared to other baselines?
- **RQ4:** For the runtime performance, is THREATKG efficient enough to be practical for a real-world deployment?

A. Evaluation Setup

The deployed server has an AMD EPYC 7282 CPU (2.80GHz) running Ubuntu 20.04 and an Nvidia GRID T4-16Q GPU with 16GB RAM. To evaluate the accuracy of THREATKG in extracting threat knowledge, a ground-truth labeled OSCTI report dataset is needed. To construct the ground truth, we manually labeled 141 reports selected from seven OSCTI sources, including: APTnotes attack reports, two threat encyclopedias, and four enterprise security blogs. These reports have diverse formats and cover a wide range threat knowledge. For entities specified in the ontology, we label them using the BIO tags. For relations, we label both the relation verbs (if exist) between the two entities for explicit relations, and the relation categories for implicit relations (we have 17 relation categories in total). Two of our authors are involved in the labeling process. They first independently labeled all the entities and relations. Then, they cross-checked each other's results and resolved any conflicts. Table I shows the statistics of our ground-truth OSCTI dataset.

Training DL-based models typically require a large dataset. However, annotating entities and relations in OSCTI reports is very expensive, especially given the wide range of knowledge types that we target. As mentioned in Section III-D1, we are faced with a unique challenge that there is no existing benchmark dataset available for the threat knowledge extraction domain. We have made our best effort to curate an OSCTI dataset at the current scale to evaluate our system.

B. Evaluation Results

1) RQ1: Accuracy of Irrelevant Report Filtering: As labeling whether a report is relevant to cyber threats or not is much easier compared to annotating entities and relations, we constructed a separate dataset that has more reports solely for evaluating the checker performance. The dataset comprises of 755 reports randomly selected from three random OSCTI sources: Securelist, Symantec Threat Intelligence, and Webroot. In the dataset, 517 reports are relevant to cyber threats and 238 reports are irrelevant to cyber threats.

OSCTI reports collected from different sources have different structures, writing styles, and focused topics. Considering the distributional shift in the training data, a classifier might benefit more from data within the same source compared with other sources. To investigate this, we ran two experiments: (1) For each source, we trained a source-specific classifier and evaluated its performance on its own source. (2) We combined all sources to train a universal classifier and evaluated its performance on each source individually. We trained a number of ML classifiers, including: Logistic Regression, Random Forest, Linear SVM, SVM with RBF Kernel, XGBoost, and LightGBM. The train/dev/test split is 70-10-20.

Table II shows the results averaged for different ML models. We have the following observations: (1) For source-specific classifiers, the average F1 scores are above 86% and the average false negative rates (FNRs) are below 3.77%. The false positive rates (FPRs) are higher. In our problem setting, a high FPR is acceptable as long as the FNR can be sufficiently low. The reason is because a high FNR means that many relevant reports (and the contained threat knowledge) are filtered out, while a high FPR just means that the system is conservative in filtering the reports. (2) The performance of the universal classifier does not benefit from more training data, and is worse than the source-specific classifiers for some sources. This verifies the distributional shift problem in different OSCTI sources that we conjectured previously. Thus, in practice, we recommend training classifiers for different sources separately to get better checker performance.

2) RQ2: Accuracy of Threat Knowledge Extraction: **Accuracy of BiLSTM-CRF Model for NER.** As our labeled dataset in Table I is a bit small for training the neural NER model, we gathered the rest reports from the same seven sources. We then applied data programming to these reports to expand the dataset. We performed two experiments (80-20 train/test split): (1) We trained the BiLSTM-CRF model and evaluated it on a test set from the same OSCTI sources. (2) We evaluated the same trained model on all other OSCTI sources (i.e., excluding the seven sources). This experiment aims to evaluate the generalizability of our model on unseen sources. Table III shows the hyperparameters of the model.

Table IV shows the averaged results for all entity BIO tags for the two settings. We can observe that in both settings, the model has good performance ($>99\%$ F1). Besides, if we exclude the "O" tags (i.e., used for other tokens that are not of interest) in the calculation, which outnumber other tags in the dataset, the model's performance is still good. These results demonstrate the model's performance and generalizability.

TABLE II: Report checker performance (averaged for different classifiers)

	Symantec Threat Intelligence				Securelist				Webroot			
Training Procedure	**Accuracy**	**F1**	**FPR**	**FNR**	**Accuracy**	**F1**	**FPR**	**FNR**	**Accuracy**	**F1**	**FPR**	**FNR**
Source-specific	93.33%	95.38%	21.21%	0.00%	81.14%	87.67%	53.62%	3.77%	78.33%	86.02%	64.10%	1.23%
Universal	94.29%	95.92%	13.64%	2.08%	80.04%	86.99%	54.35%	5.03%	73.75%	83.50%	76.92%	1.85%

TABLE III: BiLSTM-CRF hyperparameters

Hyperparameter	Value
Epochs	35
Batch size	64
Max report length	2,000
Number of hidden units	256
Embedding dimension	512
Number of LSTM layers	2
Learning rate	1e−2

TABLE IV: Entity extraction performance

	Precision	Recall	F1
Seen Sources	99.98%	99.98%	99.98%
Unseen Sources	99.83%	99.83%	99.83%

Accuracy of PCNN-ATT Model for RE. The labeled dataset in Table I contains 7308 relations. We picked 16 reports (same as the ones in Section IV-B3) and constructed the test set using the relations in them. In the remaining 125 reports, there are 1219 "non-others" relations (relations that are not "others") and 4615 OTHERS relations. This dataset is imbalanced and will negatively impact the performance of the model trained on it. Thus, we under-sampled the OTHERS relations to make the dataset more balanced. After under-sampling, there are 1732 OTHERS relations left. To further expand the dataset, we manually labeled 805 more "non-others" relations chosen from the same seven OSCTI sources. Finally, we created train/dev split of 87.5% and 12.5% respectively from the 2024 "non-others" relations and 1732 OTHERS relations.

Table V shows the hyperparameters. Table VI shows the aggregated results for all relation categories. The results (79% F1) are within our expectations as we are dealing with a challenging multi-class classification task (17 categories) and we only have a small dataset available to train the model.

Effectiveness of Data Programming. We conjecture that the reason for the current RE performance is the lack of training data. Thus, we created more training instances using data programming. We labeled 2049 more "non-others" relations and used all the 4615 OTHERS relations, and created a train/dev split of 87.5% and 12.5%. The test set is the same as the previous RE experiment (the manually labeled one).

From the results in Table VI, we can see that the RE performance is significantly improved with data programming (from 79% F1 to 85% F1). In addition, the performance for the relation types with fewer training instances in the previous experiment is also improved. For example, for the relation INJECT, in the previous experiment, the F1 is only 55% with 222 training instances. But after data programming, the model was trained on 558 instances and its F1 score is improved to 72%. These results demonstrate the effectiveness of data programming in creating training data to improve the model.

TABLE V: PCNN-ATT hyperparameters

Hyperparameter	Value
Epochs	20
Batch size	32
Size of windows in convolution layer	3
Learning rate	1
Dropout rate	0.1

TABLE VI: Relation extraction performance

	Precision	Recall	Accuracy	F1
W/O Data Programming	80%	78%	78%	79%
W/ Data Programming	85%	85%	85%	85%

3) RQ3: Comparison With Existing Security Information Extraction Approaches: To further evaluate THREATKG's effectiveness in extracting threat knowledge, we compared THREATKG with two state-of-the-art security information extraction approaches, TTPDrill [65] and EXTRACTOR [45].

We used the 16 reports that we selected for the test set for the RE performance evaluation in Section IV-B2, and evaluated these three approaches. The reports are selected to represent a wide variety of threat scenarios: (1) 8 reports that cover major OS platforms (e.g., Linux, Windows, IOS, and Android). (2) 8 reports that cover well-known APT campaigns (e.g., Stuxnet and Beapy) and common types of cyber threats (e.g., malware and cryptojacking attacks). We ran TTPDrill and EXTRACTOR on these reports. For THREATKG, we used the same model that we trained in Section IV-B2.

TTPDrill is designed to extract threat actions and map them to TTP categories, and TTPDrill does not extract entities. This differs significantly from THREATKG as THREATKG has a much wider coverage of entity and relation types. Thus, when comparing the extraction performance, we only compare the overlapping part. Specifically, we compared the threat actions extracted by TTPDrill with the relation types extracted by THREATKG. EXTRACTOR has a similar output as THREATKG's extraction module that extracts the subject-predicate-object triplets. However, different from THREATKG, EXTRACTOR only considers subjects/objects that involve IOCs, and IOCs are easy to extract using regular expressions Thus, we evaluated the relation extraction performance of EXTRACTOR based on the meaning of the extracted phrases, and compared with the relations extracted by THREATKG. It is also important to note that neither TTPDrill nor EXTRACTOR targets building an automated system that extracts threat knowledge from a large number of OSCTI reports to construct a threat knowledge graph

Table VII shows the results. We observe that: (1) The performance of relation extraction of EXTRACTOR is lower than that of ThreatKG. The reason is that EXTRACTOR is originally designed for extracting phrases that involve IOCs. (2) TTPDrill suffers from a low precision because the goal

TABLE VII: **Relation extraction performance (-#false negatives, +#false positives) of TTPDrill, EXTRACTOR, and THREATKG.**

CTI reports	# Words	Manual	TTPDrill	EXTRACTOR	ThreatKG
hunting-for-linux-library-injection-with-osquery	1431	145	(-105, +341)	(-128, +207)	(-47, +47)
android-backdoor-disguised-as-a-kaspersky-mobile-security-app-65534	233	34	(-28, +130)	(-28, +43)	(-16, +16)
peer-peer-poisoning-attack-against-kelihosc-botnet	829	43	(-38, +214)	(-31, +116)	(-6, +6)
dragonfly-energy-companies-sabotage	1095	104	(-88, +619)	(-84, +221)	(-22, +22)
android-apps-coronavirus-covid19-malicious	388	30	(-24, +105)	(-21, +59)	(-7, +7)
new-versions-of-the-iexplorer-zeroday-emerge-targeting-defence-and-industri	317	40	(-33, +99)	(-30, +55)	(-15, +15)
Trojan.Win64.Shelma	17	2	(-0, +13)	(-1, +1)	(-0, +0)
analyzing-the-security-of-ebpf-maps	1066	105	(-89, +533)	(-86, +217)	(-31, +31)
security-vpn-ios-macos	400	12	(-9, +187)	(-8, +112)	(-2, +2)
duqu-next-stuxnet	502	49	(-44, +266)	(-38, +89)	(-18, +18)
Trojan-DDoS.Win32.Nesmed	12	4	(-4, +6)	(-3, +1)	(-2, +2)
inside-geinimi-android-trojan-chapter-one-encrypted-data-and-communication	655	11	(-11, +31)	(-10, +56)	(-1, +1)
beapy-cryptojacking-worm-china	1271	123	(-104, +508)	(-102, +316)	(-34, +34)
a-few-words-about-the-hlux-botnet-29806	51	11	(-11, +41)	(-5, +11)	(-2, +2)
google-cloud-platform-security-monitoring-with-usm-anywhere	542	47	(-37, +289)	(-33, +129)	(-11, +11)
Alienvault_Scanbox	400	28	(-22, +180)	(-16, +85)	(-6, +6)
Overall Precision			**0.038**	**0.198**	**0.85**
Overall Recall			**0.199**	**0.305**	**0.85**
Overall F-1 Score			**0.063**	**0.217**	**0.85**

TABLE VIII: **Runtime performance breakdown**

<table>
<tr><th>Stage</th><th>Total Processing Time (h)</th><th colspan="3">Percentage</th></tr>
<tr><td>Porter</td><td>0.54</td><td colspan="3">0.6%</td></tr>
<tr><td>Checker</td><td>0.03</td><td colspan="3">0.0%</td></tr>
<tr><td>Parser</td><td>1.45</td><td colspan="3">1.7%</td></tr>
<tr><td rowspan="5">Extractor</td><td rowspan="5">85.26</td><td rowspan="5">97.7%</td><td>Content relevance analysis</td><td>2.1%</td></tr>
<tr><td>Dependency parsing for IOC relation extraction</td><td>83.1%</td></tr>
<tr><td>BiLSTM CRF entity extraction recognition</td><td>6.0%</td></tr>
<tr><td>Potential relation marking</td><td>0.9%</td></tr>
<tr><td>PCNN-ATT relation extraction</td><td>5.7%</td></tr>
</table>

of TTPDrill is to extract threat actions and map them to TTP categories, so it exhaustively extracts many phrases to provide enough information for the mapping part. These results demonstrate THREATKG's wide coverage of threat knowledge types.

4) RQ4: System Runtime Performance: We measured a single-process procedure for all the OSCTI reports with GPU enabled. The evaluation took 87.3 hours to finish, reaching a processing throughput of 24.7 OSCTI reports per minute. With 11 articles added to the system every day, the expected daily workload is less than half a minute.

We also provide a performance breakdown analysis in Table VIII. We notice that the extractors take most of the time and the dependency parsing is the bottleneck. A potential reason is that the sentence-wise dependency parsing for long content OSCTI report is time-consuming. As evidence, the dependency parsing for the source apt_notes with an average content length of 32503 characters takes 22.0 seconds on average (88.5% of total processing time for that source). In contrast, for the source symantec_vulnerability with an average content length of 332 characters, it takes 0.1 seconds on average (71.5% of total processing time for that source).

In summary, the evaluation results show that THREATKG is efficient enough for real-world use cases. Future efforts to further improve the runtime performance should focus on improving the efficiency of NLP dependency parsing modules.

V. DISCUSSION

Limitations and Design Alternatives. We identify several major limitations caused by the current design choices in THREATKG. First, although a fixed schema simplifies the interface design for downstream applications and makes the semantics for entities and relations clearer, information that is not considered by the schema cannot be captured by the system. In comparison, an OpenIE-like system [26], [27] can extract information based on triplets without a pre-defined schema, potentially covering more types of entities and relations. We will explore the integration of OpenIE-based extractors in the future. Second, while the modular design of having separate NER and RE models provides extensibility and robustness, without a global gradient passing mechanism, it is hard to implement an end-to-end machine learning model that is easier to manage. Third, during the system design, we assume the OSCTI sources that we choose are reliable, which might not be the case with an adversarial or compromised OSCTI publisher. An alternative is to design more complex algorithms to maintain confidence scores for all the generated facts and also revise the knowledge fusion procedure.

Downstream Security Applications. THREATKG can empower many existing downstream security applications while supporting new applications that were not possible before. Existing threat intelligence research [4], [66] has shown that individual reports often cover only partial knowledge about threat behaviors. By aggregating the knowledge gathered from multiple reports into a unified knowledge graph, THREATKG provides more comprehensive results in threat search and analysis. As THREATKG automatically extracts structured knowledge from unstructured OSCTI reports, systems and platforms that previously benefit from the structured OSCTI can also benefit from the knowledge provided by THREATKG. For example, the knowledge extracted by THREATKG can be converted into open formats like STIX [67], exchanged in platforms like AlienVault OTX [9], and integrated in existing intrusion detection systems [36], [68] and attack investigation systems [69], [70] that take IOC and STIX feeds as the input.

Research has also proposed to use the knowledge extracted from individual OSCTI reports to guide threat hunting [37]. With the aggregated knowledge provided by THREATKG, a new way of threat hunting can be enabled. For example, we can reduce the efforts of manual query construction in threat hunting, by synthesizing or suggesting queries based on the threat knowledge graph and the partial user input. We will leave these applications for future work.

VI. RELATED WORK

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

CTI Services and Platforms. Various platforms and services have been proposed to manage OSCTI. Platforms like AlienVault OTX [9], IBM X-Force [10], MISP [11], and OpenCTI [12] allow users to contribute, share, or manage OSCTI. Unlike these platforms that require users to contribute information, THREATKG gathers and aggregates threat knowledge automatically from OSCTI reports using ML and NLP techniques. There are also services, such as PhishTank [5], OpenPhish [6] and Abuse.ch [7], that provide real-time CTI feeds. However, they only focus on specific types of entities. For instance, PhishTank and OpenPhish focus on phishing URLs, and Abuse.ch focuses on malware and botnets. In contrast to them, THREATKG extracts a much wider range of entities (e.g., threat actors, techniques). Moreover, THREATKG aims to build a connected knowledge graph with semantic relationships between entities, which is not covered in existing platforms. Besides these services and platforms, research progress has been made to better analyze OSCTI reports, including understanding vulnerability reproducibility [66], and measuring threat knowledge quality (e.g., consistency, accuracy, and coverage) [4], [71]. Such research is orthogonal to THREATKG.

CTI Formats and Ontologies. There exist open standard formats such as STIX [67], OpenIOC [72], and CybOX [73] for exchanging threat intelligence. They are schemas rather than the large threat knowledge graph as constructed by THREATKG that contains the actual knowledge. The knowledge gathered by THREATKG can be easily converted into these formats for distribution. MITRE ATT&CK [24] is a knowledge base for cyber adversary behaviors based on real-world observations. It is manually curated by security experts and does not focus on automated knowledge extraction from unstructured reports as done in THREATKG. It also does not contain IOC relations. There are some cyber ontologies [28], [29], [31], [74], [75] that support reasoning, but most of them only focus on sub-domains of threat knowledge, such as IDS [74], [75] and malware behavior [28], [29]. STUCCO ontology [30] is designed to integrate both structured and unstructured data sources but lacks support for high-level threat knowledge like techniques and tactics. UCO [31] aims to provide a unified ontology but is limited to attack information without mitigation information. Furthermore, all of these ontologies do not focus on automated knowledge extraction from reports.

Note that in this work we do not focus on standardizing OSCTI as there already exist open standards like STIX and OpenIOC. We also do not focus on building a comprehensive platform like AlienVault OTX and OpenCTI for users to share and manage the OSCTI data. Instead, we focus on automatically gathering OSCTI from unstructured reports and aggregating and structuralizing it, which has not been covered in existing solutions. The structuralized knowledge can then be easily converted into standard formats like STIX, shared on platforms like AlienVault OTX, or imported to platforms like OpenCTI for knowledge management.

Threat Knowledge Extraction. Several studies have proposed to extract threat knowledge from OSCTI reports. iACE [13] extracts IOCs from security articles using a graph mining technique. ChainSmith [76] further classifies the extracted IOCs into different attack campaign stages (e.g., baiting, exploitation, installation, and command and control) using neural networks. TTPDrill [65] extracts threat actions from Symantec reports and maps them to pre-defined attack patterns. EXTRACTOR [45], ThreatRaptor [37], and HINTI [77] use various NLP techniques to extract IOC entities and IOC relations. Most of these work focus only on IOCs or IOC relations. In contrast, THREATKG covers a wider range of entities (e.g., threat actors, techniques, tools) and relations. Besides, these works only extract knowledge from a single OSCTI report. In contrast, THREATKG automatically extracts knowledge from a large volume of reports, aggregates the knowledge to construct a large threat knowledge graph, and continuously updates the threat knowledge graph by ingesting new knowledge, providing a comprehensive view of the latest threats. The scope of THREATKG is different from the scopes of these works.

General Knowledge Graphs. There are a number of knowledge graphs [38]–[43] designed for storing and representing general knowledge (e.g., people, location, organizations). Different from them, THREATKG targets automatically constructing a threat knowledge graph for security domain, by gathering and aggregating knowledge from OSCTI reports. The constructed threat knowledge graph contains both detailed threat behavior steps (e.g., IOCs and IOC relations) and the high-level threat contexts (e.g., threat actors, techniques). Such domain-specific threat knowledge is not available in existing knowledge graphs. With the threat knowledge graph, various downstream security applications can be empowered.

VII. CONCLUSION

We have presented THREATKG, a system for automated open-source cyber threat knowledge gathering and management. THREATKG automatically constructs a large threat knowledge graph from a large number of OSCTI reports using ML and NLP techniques, and provides a GUI to facilitate knowledge acquisition. THREATKG has the potential to empower a variety of downstream security applications

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