Integrating Hybrid Features in a Comprehensive CTI Dataset: Towards Enhanced Cyber Threat Attribution*

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***Abstract*—Cyber-threat intelligence (CTI) plays a pivotal role in understanding and mitigating cyber-security threats. In this paper, we present a novel dataset amalgamating hybrid features (technical and behavioral) extracted from real-world CTI reports and threat actor profiles. The dataset encompasses diverse features including tactics, techniques, and procedures (TTP), tools, malware, target country, organization, and application, as well as behavioral insights such as motivation, the operation performed, first seen, sponsor by, origin nation, outcome, and attacker skills. Leveraging this integrated dataset, we aim to empower the research community with a comprehensive resource for advancing cyber-threat attribution analysis methodologies and techniques. Our research methodology involves the extraction, and validation of hybrid features from disparate sources, followed by experimentation to demonstrate the utility and efficacy of the dataset. We anticipate that this dataset will facilitate deeper insights into cyber-threat attribution, and enhance threat attribution capabilities.**

***Index Terms*—Cyber-threat attribution (CTA), Cyber-threat intelligence (CTI), Tactics techniques and procedure (TTP), Advanced persistent threat (APT), and Incident of compromise (IoC).**

I. Introduction

Cyber-threat attribution is critical for understanding and effectively combating cyber threats. It entails attributing malicious operations to specific threat actors and providing information about their motives, capabilities, and objectives [1]. However, the attribution process is complicated due to the dynamic nature of cyber threats and the scarcity of comprehensive datasets for training and evaluation. Existing datasets frequently lack diversity and realism, which impedes the development and validation of attribution models. To close this gap, we present a method for creating manufactured datasets specifically for cyber-threat attribution tasks. Our approach includes a variety of parameters relevant to cyber threat attribution, allowing for complete study and evaluation [**?**].

Accurate attribution enables organizations to respond more effectively, anticipate new threats, and strengthen their defenses. However, a lack of realistic and diverse datasets impedes the development of strong attribution models. Fabricated dataset production provides a solution by allowing researchers to produce custom datasets that fulfill unique study needs [3], [4].

In recent years, the proliferation of cyber threats has highlighted the urgent need for strong cyber-security measures to protect digital assets, sensitive information, and critical infrastructure. As organizations rely more on digital technology and networked systems, they confront a broader range of cyber hazards, including malware infections, data breaches, phishing attacks, and insider threats. To address these difficulties, information security researchers and practitioners are always working to build effective cyber-security solutions, which range from intrusion detection systems (IDSs) and firewalls to malware detection tools and behavioral analytics platforms [5], [6].

The availability of high-quality datasets that accurately reflect real-world cyber threats and attack scenarios is critical for developing and evaluating such cyber-security solutions. Real-world cyber-security datasets frequently contain sensitive information, such as personally identifiable information (PII) and proprietary system configurations, making them difficult to share and use for research purposes while maintaining data privacy and compliance with regulations like GDPR and HIPAA [7], [8].

Certain types of cyber dangers, such as advanced persistent threats (APTs) and zero-day exploits, are uncommon and may not be sufficiently represented in existing datasets, resulting in data imbalance and difficulty when building strong cyber-security models. The cyber-security threat landscape is always changing, as threat actors use sophisticated strategies and approaches to avoid discovery and exploit weaknesses. As a result, static databases might quickly become obsolete, failing to capture developing risks and attack routes [9].

To solve these issues and improve cyber-security research and analysis, researchers have employed manufactured dataset-generating techniques. Fabricated datasets are synthetic datasets built using a variety of methods, including simulation, emulation, generative models, and rule-based approaches, to simulate real-world cyber risks and attack scenar-

ios while maintaining data privacy, scalability, and adaptivity. Researchers can overcome the limits of real-world datasets by creating manufactured datasets, which provide controlled environments for training, testing, and assessing cyber-security systems [9].

Finding uses and benefits for faked datasets in many areas of information security, such as intrusion detection, malware analysis, phishing detection, and behavioral analytics, is a difficult issue. Furthermore, we discuss the obstacles and considerations related to manufactured dataset development, such as guaranteeing data realism, resolving ethical concerns, and assessing dataset quality and effectiveness. Fabricated datasets play an important role in enhancing cyber-security research and practice by providing academics and practitioners with significant tools and strategies for creating synthetic data tailored to their individual needs and aims [10].

The contribution of this research work is that it has generated a fabricated dataset from unstructured CTI reports, a threat actor encyclopedia. The dataset contains hybrid features (technical and behavioral).

This paper is formatted as follows: Section 1 is about the introduction, whereas Section 2 elaborates on related work. Section 3 defines the problem statement. Section 4 outlines the research methodology. The results are defined in section 5. The advantages of the generated dataset are proposed in Section 6. The conclusion and future work are discussed in Section 7.

II. Related Work

This research article [11] presents a comprehensive framework for cyber-threat attribution in cyber-threat intelligence. The framework encompasses various attribution techniques.

This research article [12] proposes a novel approach for generating synthetic datasets for cyber-threat attribution using generative adversarial networks (GANs).

This research article [13] focuses on the generation of realistic synthetic datasets tailored for cyber-threat attribution research. The authors propose a methodology for synthesizing datasets that capture the complexity and diversity of real-world cyber-threat scenarios.

This comparative study [14] evaluates attribution models using fabricated datasets generated specifically for cyber-threat attribution research.

This paper [15] presents a novel approach for generating realistic synthetic datasets for cyber-threat attribution research using simulation techniques.

This research article [16] proposes an integrated approach for enhancing cyber-threat attribution research through synthetic data generation and adversarial testing.

This study [17] focuses on bench-marking cyber-threat attribution techniques using fabricated datasets and ground truth validation.

This paper [18] proposes a deep learning-based approach for synthetic data generation tailored for cyber-threat attribution analysis.

This paper [19] presents an approach for synthesizing realistic datasets for cyber-threat attribution by leveraging domain knowledge and expert insights.

This research article [20] proposes a machine learning-based approach for synthetic data generation tailored for cyber-threat attribution modeling.

This paper [21] focuses on the creation of transparent and interpretable synthetic datasets for cyber-threat attribution research. The authors develop methodologies for generating synthetic datasets that maintain transparency and are explainable.

This study [22] evaluates synthetic data generation techniques for cyber-threat attribution research. The authors compare and analyze various approaches for generating synthetic datasets, including rule-based systems, generative models, and simulation techniques.

This research article [23] presents a method for generating synthetic datasets for intrusion detection using generative adversarial networks (GANs). The authors propose a GAN-based framework to synthesize realistic network traffic data, including normal and attack behaviors.

This survey paper [24] provides an overview of synthetic data generation techniques for cyber-security applications. The authors review various approaches for generating synthetic datasets, including rule-based systems, generative models, simulation techniques, and machine learning algorithms.

This study [25]benchmarks synthetic data generation techniques for malware analysis. The authors evaluate various approaches for generating synthetic datasets.

This research article [26] explores the use of synthetic datasets for adversarial testing of cyber-security systems. The authors develop methodologies for generating synthetic datasets that mimic diverse cyber-attack scenarios and evasion techniques.

This research paper [27] presents a method for generating custom datasets tailored for anomaly detection in industrial control systems (ICS). The authors propose a framework for collecting and labeling data from ICS environments, including process data, sensor readings, and control commands.

This paper [28]explores the use of differential privacy for secure and private data generation in cyber-security applications. The authors develop techniques for synthesizing synthetic datasets that preserve the privacy of sensitive information while retaining utility for cyber-security analysis.

This research article [29] focuses on the creation of custom datasets for behavioral analysis of insider threats in enterprise networks. The authors develop methodologies for collecting and labeling data representing user behaviors, network activities, and system events.

This study [30] explores the use of crowd-sourcing for data generation in cyber-security research and analysis. The authors develop platforms and methodologies for collecting data from a diverse pool of contributors, including security professionals, researchers, and end-users. This paper [31] introduces a simulation-based approach for generating fabricated datasets tailored for cyber-security training and evaluation purposes. The authors develop simulation environments that mimic real-world cyber-attack scenarios.

This research article [32]presents a method for synthetic data

generation using generative adversarial networks (GANs) for information security applications. The authors leverage GANs to generate synthetic datasets that capture the underlying distributions.

This paper [33] proposes a rule-based approach for fabricating datasets tailored for evaluating intrusion detection systems (IDSs). The authors define rules and heuristics for generating synthetic instances representing normal and malicious network traffic patterns.

This study [34] introduces a dynamic synthetic data generation approach for cyber-security research and analysis. The authors develop algorithms that adaptively generate synthetic data based on evolving cyber-security threats and trends.

This research article [35] presents hybrid synthetic data generation techniques for information security applications. The authors combine multiple approaches, including simulation, emulation, and machine learning-based methods, to generate synthetic datasets that capture diverse security scenarios and contexts.

This paper [36]discusses cyber-threat attribution methodologies leveraging unstructured CTI reports. The primary objective is to summarize various approaches and techniques used for attributing cyber threats to their sources or perpetrators by analyzing unstructured CTI data. As technology advances rapidly [37], discerning the culprits responsible for cyber-attacks becomes increasingly intricate. However, these methods lack insight into the attacker's context and motives, necessitating more nuanced attributes.

III. Problem Statement

The primary challenge in cyber-threat attribution research is the lack of access to comprehensive and representative datasets containing diverse and realistic attacker attribution. Existing datasets often lack essential features and labels required for attribution tasks, hindering the development and evaluation of attribution algorithms. Dataset generation from real data offers a promising solution to address these challenges having hybrid features by providing researchers with extracting data from unstructured CTI reports and threat actor profiles.

IV. Research Methodology

Our research methodology comprises several key steps. Firstly, we collect a corpus of CTI reports containing unstructured text data describing cyber incidents and attacks. From these reports, we extracted technical features such as TTP, tools, malware, target country, organization, and application using natural language processing techniques. Simultaneously, we obtained behavioral features from a separate dataset known as the threat actor encyclopedia, which contains structured information about threat actors, including motivation, first seen, operation performed, sponsor by, outcome, and origin country. Next, we integrate these hybrid features (technical and behavioral) into a unified dataset, ensuring consistency and compatibility across different sources. To validate the dataset, we employ rigorous data cleaning and prepossessing techniques, followed by exploratory data analysis to identify patterns and correlations. Finally, we conducted experiments to demonstrate the utility and effectiveness of the dataset in various cyber threat analysis tasks. Our methodology comprises several steps:

A. Data Collection

Identified and gathered relevant data from unstructured CTI reports published by well-known vendors and threat actor encyclopedia. Collected raw data encompassing indicators of compromise (IoCs), context, and motivation of the attacker. In this step, approximately 27,000 CTI reports have been gathered for experimentation, encompassing twelve cyber-threat actors. For extracting behavioral features threat actor encyclopedia has been used. In this phase, relevant CTI reports contain detailed descriptions of cyber incidents, attacks, and adversary behaviors. Extracted unstructured text data from the CTI reports, including narrative descriptions of attack techniques, tools, malware, target country, organization, and application. It also contains behavioral features extracted from the threat actor encyclopedia. The dataset is publicly available at Git Hub.

B. Features Description

A brief description of each feature is defined below. Motivation: The underlying motive or purpose behind the cyber-attack, such as financial gain, espionage, or sabotage. Operation Performed: The specific actions or operations performed by the attacker during the cyber-attack, such as data ex-filtration, system compromise, or denial of service. First Seen: This attribute tells when this threat actor was first seen in cyberspace.

Sponsored By: The entity or organization sponsoring or backing the cyber-attack, which could be state-sponsored, financially motivated, or ideologically driven. Origin Country: The country or region from which the cyber-attack originates, providing geopolitical context and attribution clues.

Outcome: The outcome or impact of the cyber-attack, such as data breach, or service disruption.

Attacker Skills: Attacker skills refer to the expertise, knowledge, and capabilities possessed by the threat actor or cyber attacker. These skills encompass a wide range of technical proficiency's, including programming languages, exploitation techniques, network protocols, cryptography, and social engineering tactics.

Tactics, Techniques, and Procedures (TTPs): Tactics, techniques, and procedures (TTPs) represent the methods, strategies, and approaches employed by threat actors to conduct cyber-attacks. TTPs encompass a broad spectrum of activities, including reconnaissance, initial access, privilege escalation, lateral movement, data exfiltration, and persistence.

Malware: Malware, short for malicious software, refers to any software intentionally designed to cause harm, damage, or unauthorized access to computer systems, networks, or data.

Tools: Tools in the context of cyber-threat attribution refer

to the software applications, utilities, scripts, or frameworks used by threat actors to facilitate various stages of the cyber-attack lifecycle. These tools can include network scanning tools, penetration testing frameworks, exploit kits, command-and-control (C2) servers, remote access Trojans (RATs), and post-exploitation tools. Target Organization: The target organization refers to the entity or entity that is the intended victim of a cyber-attack. This could be a corporation, government agency, educational institution, non-profit organization, or individual entity.
Target Country: The target country refers to the geographical location or jurisdiction of the target organization or victim of a cyber-attack.
Target Application: The target application refers to the software, platform, or system targeted by a cyber-attack. This could include web applications, enterprise applications, operating systems, cloud services, mobile applications, or internet-of-things (IoT) devices.

C. Data Integration/ Pre-processing and Cleaning:

Standardized data formats and structures are applied to the dataset to ensure consistency across different sources. Removed duplicate and missing entries and irrelevant data that do not contribute to the research objectives. Sanitized sensitive information to protect privacy and confidentiality. Performed data cleaning and prepossessing steps to address missing values, outliers, noise, and formatting issues. Normalized numerical features and encoded categorical variables to prepare the dataset for analysis and modeling. Merge the hybrid features into a unified dataset, aligning common identifiers and resolving any discrepancies or inconsistencies.

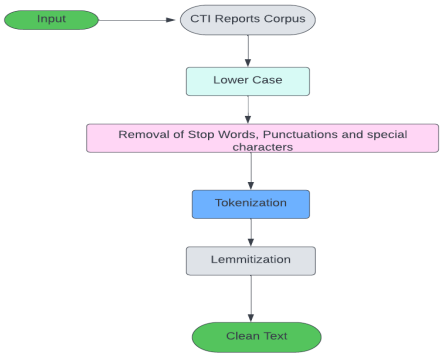

Fig. 1. Text Pre-processing.

D. Feature Extraction

Extracted meaningful features from the raw data. Transformed raw data into feature vectors suitable for machine learning algorithms, considering both categorical and numerical attributes.
i. Technical Feature Extraction Utilized natural language processing (NLP) techniques such as removal of stop words, punctuation, lemmatization, and part-of-speech tagging to extract technical features from the text data. Identify and extract tactics, techniques, and procedures (TTP) employed by threat actors, including common attack vectors, exploitation methods, and post-compromise behaviors. Extract information about tools and malware used in cyber-attacks, including names, versions, functionalities, and associated indicators of compromise (IOCs). Capture details about the target environment, such as the geographical location (country), industry sector (organization), and specific applications or systems targeted by the attacks.
ii. Behavioral Feature Extraction Obtained a dataset of threat

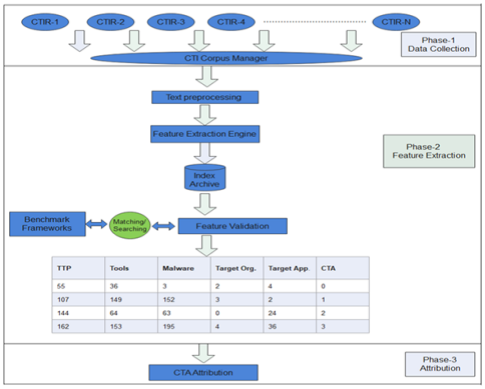

Fig. 2. Technical feature extraction.

actor profiles from reputable sources like the threat actor encyclopedia. Extract structured attributes from the threat actor profiles, including motivation (e.g., financial gain, espionage, hacktivism), first seen in cyber activity, sponsorship or affiliation with known groups or organizations, and origin country or region. Normalize and categorize behavioral attributes to ensure consistency and compatibility with the technical features extracted from the CTI reports.

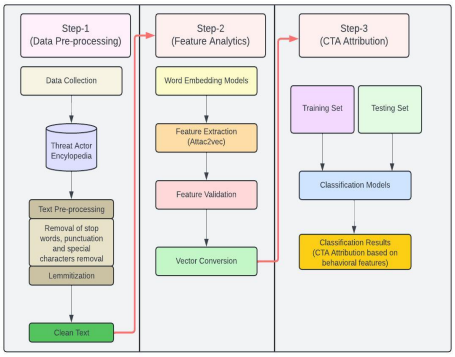

Fig. 3. Behavioral feature extraction.

E. Dataset Validation

Conduct exploratory data analysis (EDA) to gain insights into the distribution, diversity, and characteristics of the inte-

grated dataset. Visualize key relationships and patterns within the dataset using descriptive statistics, histograms, heatmaps, scatter plots, and other visualization techniques. Validate the integrity and quality of the dataset through expert review, domain knowledge validation, and comparison with ground truth or external benchmarks.

V. Results/Experimentation

Our experiments demonstrated the effectiveness of this dataset for cyber-threat attribution. We observed that attribution algorithms trained on the generated data achieve competitive performance compared to those trained on real-world datasets. The synthetic data accurately captures the diversity and complexity of cyber-attacks, allowing for robust evaluation of attribution techniques. Furthermore, sensitivity analysis reveals the impact of different features on the accuracy of attribution results, providing valuable insights for future research.

A. Experimental Setup

We implemented our methodology using Python programming language, leveraging various libraries such as Pandas, NumPy, and Scikit-learn for data manipulation, synthesis, and evaluation. The dataset generation process involved real-world threat intelligence reports and threat actor profiles.

B. Evaluation and Validation

We conducted extensive experimentation to evaluate the quality and effectiveness of this dataset. This includes assessing the diversity, realism, and utility of the data for cyber-threat attribution tasks. The dataset is split into training, validation, and testing sets to assess the performance of attribution models and techniques. Used cross-validation techniques to evaluate model generalization and robustness. Employed appropriate metrics for performance evaluation, such as Accuracy, Precision, Recall, and F1-measure. These metrics provide insights into the performance of attribution algorithms in correctly identifying cyber threat actors and their associated attributes.

C. Dataset Preparation

Split the integrated dataset into training (70%), validation (15%), and test (15%) sets to ensure robust model evaluation. Stratify the splits to preserve class distributions and ensure representative samples for each category of cyber threats. Perform feature scaling or normalization to bring all features to a similar scale and mitigate the impact of outliers.

D. Performance Comparison

We compared the performance of attribution algorithms trained on the fabricated dataset against those trained on real-world datasets. For this experiment, we utilized a variety of machine learning and deep learning models, including Random Forest, Support Vector Machine (SVM), and long short-term memory (LSTM) [36, 37].

TABLE I
Technical Feature Results.

Algorithm	Accuracy	Precision	Recall
Random Forest	96.6	96.68	95.75
Decision Tree	81	84	83
SVM	81	82	81

TABLE II
Behavioral Feature Results.

Algorithm	Accuracy	Precision	Recall
Random Forest	83	85	84
Decision Tree	91	94	92
SVM	87	91	90
LSTM	96	97	92

E. Baseline Model Development

Implement baseline machine learning models using traditional algorithms such as decision trees, random forests, and support vector machines. Train the baseline models using the training data and evaluate their performance on the validation set using metrics like accuracy, precision, recall, and F1-measure [25,47]. Analyze the baseline model results to establish a benchmark for comparison with more advanced models incorporating integrated technical and behavioral features.

F. Feature Selection Analysis

Next, we conducted a feature-important analysis to identify the most significant attributes contributing to cyber-threat attribution. We employed techniques such as PCA and genetic algorithms to quantify the impact of individual features on the predictive performance of attribution models.

G. Sensitivity Analysis and Robustness Testing

Conducted sensitivity analysis to assess the robustness of models to variations in input data, feature representations, and modeling assumptions. Evaluated model performance under different scenarios, including adversarial attacks, data perturbations, and changes in threat landscape characteristics.

VI. Conclusion and Future Work

In conclusion, we present a comprehensive dataset integrating hybrid features extracted from real-world CTI reports and threat actor profiles. By combining these diverse sources of information, our dataset offers a holistic perspective on cyber threat actors, enabling more effective threat analysis and mitigation strategies. We believe that this dataset will serve as a valuable resource for researchers, practitioners, and policymakers in advancing cyber-security research and enhancing the resilience of digital ecosystems against evolving threats. Looking ahead, we encourage further research and collaboration to expand and refine the dataset, ensuring its relevance and utility in addressing emerging cybersecurity

challenges.

In future work, we plan to further refine our methodology, explore additional techniques for enhancing dataset realism, and investigate the application of the dataset in developing advanced attribution models capable of addressing emerging cyber threats.

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