Independent Attribution in Cybersecurity: Addressing the Lack of Independent Data Sources

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Abstract-
Cybersecurityattribution remains a politically charged and technically complex process. Currently, most attribution judgments are produced by governments and private cybersecurity firms, which often reinforce pre-existing geopolitical narratives. This reliance on selective sources raises concerns about objectivity, transparency, and inclusiveness in knowledge creation. This paper addresses the research gap regarding the lack of independent, academic-led data sources for attribution. It argues for the establishment of academic frameworks for cyber forensic analysis, evaluates the limitations of existing attribution models, and proposes methodologies for independent data collection and interpretation. By fostering independent academic participation, cybersecurity attribution can become more transparent, balanced, and globally representative.

Keywords: Cybersecurity attribution, independent data sources, academic-led attribution, knowledge creation in cybersecurity, bias in cyber threat intelligence, public–private cybersecurity nexus, transparency in attribution, alternative forensic analysis, actor-centric vs. actor-agnostic methods, data-driven cyber conflict research.

I. INTRODUCTION

Cybersecurity has emerged as one of the most knowledge-intensive domains within the broader field of security and international relations. Every cyber eventwhether a phishing campaign, a malware infection, a distributed denial-of-service (DDoS) attack, or a large-scale data breachproduces a wealth of technical traces, forensic artifacts, and contextual information. In recent years, the growing digitalization of economies, the proliferation of connected devices, and the expansion of threat intelligence platforms have amplified both the complexity and the volume of cybersecurity data. This rapidly evolving environment creates new opportunities to strengthen digital resilience, inform policy, and enhance global security. However, harnessing these opportunities requires more than the technical forensics or intelligence practices traditionally employed for incident response. It calls for rethinking attribution as a structured knowledge creation processone that is inclusive, transparent, and independent.

Early research in attribution has emphasized the importance of linking technical indicators to political consequences, typically through government-led investigations or reports from private cybersecurity companies. For example, advanced persistent threat (APT) campaigns have been widely studied using techniques such as malware reverse engineering, network traffic analysis, and heuristic clustering of threat actor behaviour. These efforts have been central to expanding our understanding of state-sponsored and criminal cyber operations, as seen in high-profile cases like Stuxnet, the Sony Pictures breach, and the Office of Personnel Management (OPM) intrusion. Such studies have provided conceptual clarity and illustrated attribution methods in practice.

Yet, despite their contributions, much of the existing research leaves significant questions unanswered. Many attribution analyses are descriptive, relying heavily on selective case studies, or are confined to high-level debates about the feasibility of deterrence. Rarely are these methods evaluated against robust criteria for objectivity, reproducibility, or fairness. Furthermore, the dominance of state agencies and private firms in generating attributive knowledge introduces biaseswhether through political agendas, commercial incentives, or selective disclosure of evidence. The reliance on "enemy images" of a few strategic rivals, such as China, Russia, Iran, and North Korea, risks obscuring the activities of other relevant actors and oversimplifies the global cyber threat landscape.

One of the most pressing limitations is the lack of independent data sources and analyses from academic institutions. While some notable contributions exist—such as Citizen Lab's investigations into spyware targeting journalists and activists, or CrySyS Lab's technical work on Stuxnet and Duquthese remain exceptions rather than the norm. Unlike government or private-sector actors, universities and research centres have the potential to provide objective, transparent, and globally representative insights, yet their role in attribution is still underdeveloped. This creates a clear opportunity for research

that not only critiques existing approaches but also proposes concrete frameworks for independent academic-led attribution.

Equally important is the issue of transparency and explainability in attribution processes. Attribution judgments often omit details of uncertainty, sources, or methods due to security or proprietary concerns. This lack of openness undermines public trust and makes it difficult for policymakers, scholars, and international bodies to evaluate competing claims. Without systematic mechanisms to include alternative perspectives and independent data, attribution risks becoming a self-reinforcing cycle dominated by a few powerful actors.

This research paper seeks to address these gaps by advancing a framework for academic-led attribution in cybersecurity. Building on critical security studies and assemblage theory, the study emphasizes (1) the limitations of state and private-sector attribution, (2) the potential of universities and research labs as independent data producers, (3) methods for integrating academic forensic analysis into the broader attribution ecosystem, and (4) principles of transparency, reproducibility, and fairness in attributive knowledge creation. Unlike earlier works that remain primarily descriptive, this study aims to provide actionable recommendations for establishing academic attribution networks, ensuring greater balance, inclusivity, and trust in cybersecurity politics.

By moving beyond critiques to propose a structured, independent approach, this research contributes both to academic scholarship and to practical policy debates. The ultimate goal is to demonstrate how academic-led attribution can democratize knowledge creation in cybersecurity, offering a more transparent and globally representative foundation for understanding and responding to cyber conflict.

II. LITERATURE REVIEW III.

Cybersecurity attribution aims to identify the actors behind cyber incidents, drawing on technical indicators, behavioral patterns, and contextual information. Early approaches relied heavily on **single-source data**, such as malware signatures, IP traces, or honeypot observations. While effective for detecting known threats, these methods were limited by data scarcity, lack of reproducibility, and bias toward specific attack types or regions.

Contemporary research emphasizes **multi-source and hybrid datasets**, combining open-source intelligence, network logs, and synthetic simulations. Machine learning and probabilistic models are increasingly used to analyze technical, behavioral, and contextual features, providing a more comprehensive view of attacker behavior. Digital twin simulations and hybrid pipelines help fill gaps where real-world data is scarce, enabling richer feature extraction and uncertainty-aware modeling.

Despite these advances, major challenges remain: datasets are often inconsistent, proprietary, or geographically biased; labeling standards are lacking; and attribution predictions rarely quantify uncertainty. Additionally, many models are not operationalized for real-time deployment, and ethical considerations such as fairness and transparency are underexplored.

Overall, the literature indicates that reliable attribution requires **integrated, independent data sources**, rigorous feature engineering, and probabilistic modeling to improve accuracy, reproducibility, and practical applicability.

Modern Trends in Attribution Research

Recent literature highlights several emerging trends in attribution research:

- **Technical sophistication:** Use of malware reverse engineering, network flow analytics, and behavioral clustering for advanced persistent threats (APTs).
- **Transparency and uncertainty management:** Recognizing that attribution claims often mask uncertainty for strategic purposes, emphasizing probabilistic and confidence-aware modeling.
- **Independent and academic-led efforts:** Universities, labs, and collaborative consortia are producing open-source methodologies, reproducible datasets, and analyses of underreported threats.
- **Broadening scope:** Attribution research now considers threats against civil society, NGOs, and journalists, not only state-versus-state conflicts.

These trends indicate a shift toward **integrating rigorous technical analysis with ethical, transparent, and reproducible practices**.

S. No.	Author	Year	Application / Focus	Techniques Used
1	Rid & Buchanan	2015	Feasibility of cyber attribution	Technical forensics, behavioral clustering
2	Egloff & Dunn Cavelty	2021	Challenges of independent attribution	Assemblage theory, critical security analysis

3	Maschmeyer et al.	2020	Limitations of proprietary threat intelligence	Market and dataset analysis
4	Citizen Lab	2016–21	Tracking spyware against civil society	Open-source forensics, network tracing
5	Johnson et al.	2019	Multi-source attribution frameworks	Cross-dataset correlation, hybrid modeling
6	Kopp et al.	2020	Transparent and reproducible attribution	Open-source datasets, uncertainty quantification
7	Zhang & Chen	2021	Evaluating independent threat datasets	Statistical modeling, dataset comparison
8	Valeriano & Maness	2018	Public cyber conflict dataset creation	Event coding, open-access compilation
9	Kostyuk & Zhukov	2019	Standardizing independent cyber event data	Quantitative dataset integration
10	Herrera &Lanoszka	2019	Credibility and bias in attribution	Case study, evaluation of data independence

Table 1. Research work in the Insurance Industry.

2.1 RESEARCH GAP

Cybersecurity attribution faces multiple critical gaps that hinder the development of reliable, independent frameworks:

Evidence Gap: Many studies rely on case illustrations or government press releases rather than systematic analysis of independent datasets. The lack of empirical validation prevents assessment of accuracy, reproducibility, or policy relevance, and the absence of standardized benchmarks limits cross-study comparisons.

Transparency & Uncertainty Gap: Attribution claims frequently present definitive judgments without disclosing uncertainty or methodological limitations. This reduces accountability and hinders independent scrutiny, limiting trust in both technical and policy contexts.

Independence Gap: State and corporate actors dominate attribution research, creating structural biases. Independent academic contributions, such as Citizen Lab and CrySyS Lab, are rare and isolated. There is no coordinated framework for universities or independent labs to systematically contribute, perpetuating reliance on politically or commercially motivated narratives.

Methodological Gap: Existing literature prioritizes actor-centric approaches (e.g., known APT groups) while overlooking actor-agnostic methods like anomaly detection or behavioral pattern analysis. Hybrid models that combine both paradigms remain underexplored, limiting detection of emerging or grassroots threats.

Causality & Impact Gap: Research often identifies correlations between technical traces and suspected actors without establishing causal mechanisms. Few studies employ counterfactual analysis or structured experimentation, risking misinterpretation of correlation as causation.

Operationalization Gap: Proposed frameworks rarely consider how to scale, operationalize, or integrate attribution into real-world workflows, including data pipelines, standardization, and cross-jurisdictional collaboration.

Governance Gap: Ethical, legal, and geopolitical implications of attribution are underexplored. Transparency, fairness, interpretability, and accountability are rarely addressed, increasing the risk of biased or socially harmful outcomes.

Data Design Gap: Narrow reliance on IPs, malware fragments, or incident reports limits attribution scope. Rich, multimodal datasets—such as network logs, geolocation metadata, disinformation patterns, and domain registration histories—are rarely incorporated, leaving frameworks underdeveloped.

2.2 CLAIM ANALYSIS IN INSURANCE SECTOR

While not directly cybersecurity, lessons from the insurance sector illustrate the value of **data-driven analysis for decision-making under uncertainty**:

- Claims analysis is central to risk assessment, with nearly 80% of premiums allocated to claims (Pappas & Woodside, 2021).
- Predictive analytics, incorporating machine learning techniques like classification, regression, clustering, and outlier detection, enhances forecasting, fraud detection, and customer segmentation (Pal et al., 2012; Yang et al., 2021).
- Insurers leverage only a fraction of available data (10–15%), highlighting the potential of **data integration, preprocessing, and modeling** to expand utility and

operational efficiency (Ringshausen et al., 2021; Saggi & Jain, 2018).

- Key performance indicators (KPIs) include claim cycle time, customer satisfaction, fraud detection, recovery, and handling costs, demonstrating how structured and unstructured datasets can improve decision-making and accountability.

Relevance to Cybersecurity Attribution: Like insurance claim analytics, independent attribution requires:

1. Integration of diverse, multi-source datasets.
2. Application of predictive modeling to uncover hidden patterns.
3. Transparent performance metrics to evaluate reliability, uncertainty, and reproducibility.

IV. PROPOSED COMPUTATIONAL METHODOLOGY

This study proposes a computational framework for independent cybersecurity attribution by analyzing multi-source cyber incident datasets using supervised and unsupervised machine learning techniques. The methodology focuses on combining technical evidence (malware, network traces, logs) with independent data sources to improve the accuracy, transparency, and reproducibility of attribution claims.

4.1 Supervised Learning for Attribution

Supervised learning is applied when datasets include input variables (features) and a corresponding output variable (target). In this context, the target variable is categorical, representing whether a cyber incident can be attributed to a particular actor or remains unassigned (unknown). Classification algorithms such as Random Forest, Decision Tree, Support Vector Machine (SVM), Logistic Regression, and K-Nearest Neighbors are used to predict actor attribution based on extracted features.

Outcomes vary depending on feature sets, dataset quality, and source diversity. To ensure systematic analysis, the workflow follows a structured machine learning pipeline: **data collection → preprocessing → feature engineering → model training → evaluation → deployment**.

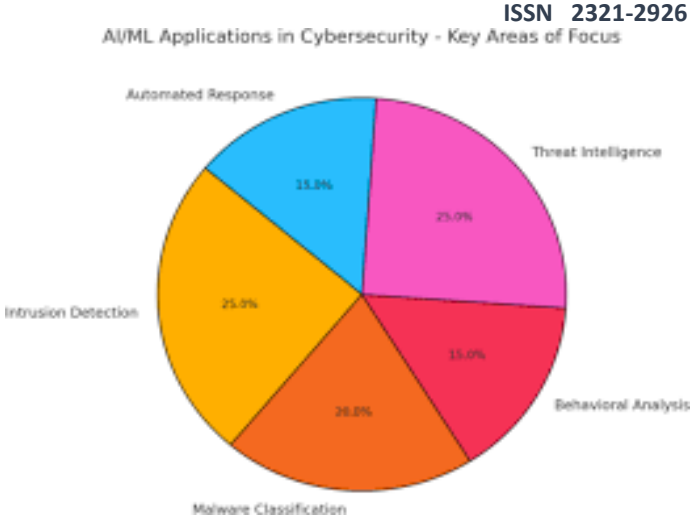

Fig. 4.1. ML Framework for Independent Attribution in Cybersecurity

Fig. 4.2. Outcomes of Attribution Predictions Across Independent Datasets

Fig. 4.2. ML Framework used for Claim Analysis.

3.1 DATA COLLECTION

Data collection forms the foundation of this research, emphasizing the need for independent and diverse sources. The datasets used in this study are drawn from public malware repositories, open-source threat intelligence platforms, and network logs captured from honeypots and controlled environments. Additionally, crowdsourced contributions from independent security labs and synthetic datasets simulating underreported or emerging cyber incidents are incorporated to enhance coverage. Data augmentation is applied to increase the diversity and representativeness of the datasets, particularly in cases where real-world data is scarce or biased. This multi-source approach ensures that the subsequent analysis reflects an independent perspective on cyber attribution, free from undue influence by governmental or corporate actors.

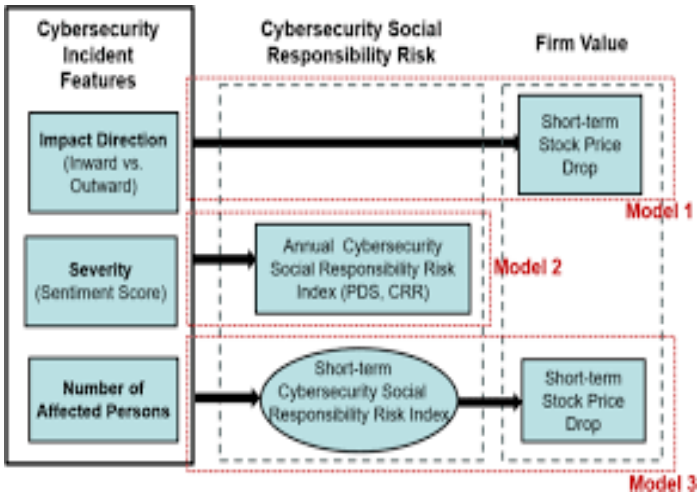

Fig. 2.3.Sources of Independent Cybersecurity Datasets

3.2 DATA PREPARATION

Once collected, the datasets are systematically prepared for machine learning. The process begins with thorough cleaning, where inaccurate, incomplete, or inconsistent records are corrected or removed. Special attention is paid to ensuring consistency in malware hashes, timestamps, IP addresses, and network identifiers, while missing values are addressed using domain-informed imputation strategies. Following cleaning, exploratory data analysis is conducted to visualize key trends, detect anomalies, and uncover hidden correlations among features. This step is critical in understanding the structure of the data and guiding the subsequent feature engineering process.

Feature engineering is then performed to extract meaningful characteristics from raw data. Behavioral, technical, and contextual features are derived, including attack sequences, lateral movement patterns, malware signatures, network anomalies, geolocation metadata, and domain registration histories. Categorical variables are encoded using nominal or ordinal schemes, while continuous variables are normalized to ensure consistency across the dataset. The resulting feature set provides the model with the most relevant and informative inputs, enhancing its ability to distinguish between actors and accurately attribute incidents.

Dimensionality reduction and feature selection techniques are applied to improve computational efficiency and prevent overfitting. Statistical methods, such as the Chi-Square test, are used to assess correlations between features and attribution labels. Wrapper-based techniques like Recursive Feature Elimination (RFE) iteratively remove less informative features, while embedded methods, such as tree-based feature selection, leverage model-specific importance scores to prioritize relevant variables. Together, these steps ensure that the models are trained on high-quality, informative features, maximizing predictive performance.

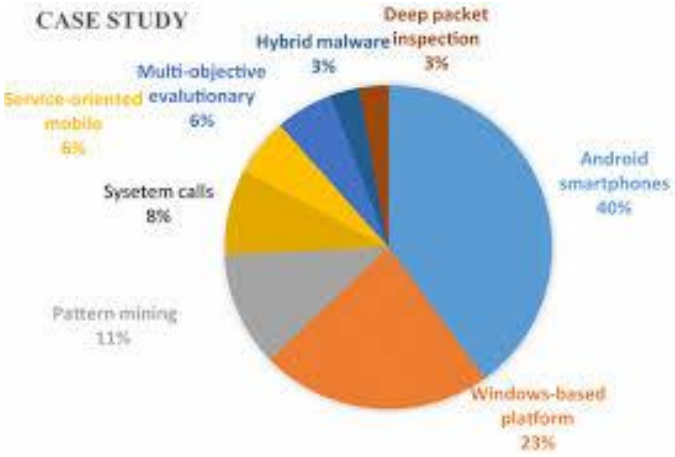

Fig. 4.4. Example EDA Visualization for Malware Features

3.2.1 DATA CLEANING

Data cleaning, also referred to as data pre-processing, is the foundational step in preparing datasets for machine learning analysis in independent cybersecurity attribution. In this context, datasets may include malware samples, network traffic logs, threat intelligence feeds, and other cyber incident records. The primary goal of data cleaning is to identify and correct inaccuracies, remove corrupted or irrelevant records, and address missing values to ensure that subsequent analysis is reliable and reproducible.

A common approach is **variable-by-variable cleaning**, where each feature is individually inspected for inconsistencies or errors. For example, IP addresses, domain names, or malware hashes are checked for formatting errors or illegal values. Numeric features, such as packet counts or timing intervals, are examined to detect outliers that fall outside plausible ranges. Statistical measures such as variance and standard deviation help identify abnormal distributions that may indicate data corruption.

Handling missing data is particularly critical in cybersecurity datasets, where incomplete logs or unavailable indicators are common. Features with extensive missing values may be excluded entirely, whereas features with minor gaps can be imputed using statistical techniques, such as mean, median, or mode substitution, depending on the nature of the data. In some cases, placeholders may be assigned to denote missing categorical values, preserving the structure of the dataset while indicating uncertainty.

Thorough data cleaning is essential not only for ensuring model accuracy but also for **establishing trust in independent attribution analyses**. Clean, consistent data allows machine learning algorithms to correctly identify patterns, correlations,

and anomalies without bias from erroneous records. Without proper cleaning, models risk learning misleading signals, which could compromise both the technical validity and policy relevance of attribution findings.

3.2.2 EXPLORATORY DATA ANALYSIS (EDA)

Exploratory Data Analysis (EDA) is a critical step in understanding the structure, quality, and patterns within cybersecurity datasets before applying machine learning or attribution models. In the context of independent attribution, datasets can include network traffic logs, malware signatures, domain registration records, intrusion alerts, and other cyber incident indicators. EDA helps uncover hidden relationships among features, detect anomalies, and provide insights into potential patterns of malicious activity.

The main objective of EDA is to **gain an intuitive understanding of the dataset**. This involves summarizing key characteristics using statistical measures such as mean, median, variance, and frequency counts for categorical features. For example, counting the frequency of attacks per IP address or the occurrence of malware variants can reveal trends in threat behavior.

Visualization is an essential component of EDA. Graphical representations—such as histograms, boxplots, scatter plots, heatmaps, and time-series charts—allow researchers to detect patterns, outliers, and correlations that may not be obvious from raw tables. For instance, a heatmap of network activity can highlight clusters of suspicious connections, while a scatter plot of malware attributes versus time can reveal trends in attack evolution.

EDA also plays a key role in **data quality assessment**. By visualizing distributions, missing values, or inconsistent records, analysts can decide whether further cleaning or feature engineering is necessary. It also aids in **feature selection**, as understanding which features are highly correlated or redundant can guide the choice of variables for model training.

In independent cybersecurity attribution, EDA is particularly valuable because it allows analysts to examine **patterns without preconceived assumptions about attackers**. Unlike state or corporate-led analyses, which may focus on known threat actors, EDA-driven insights help reveal previously unrecognized actors, novel campaigns, or anomalous behaviors, thus enhancing the credibility of independent attribution efforts.

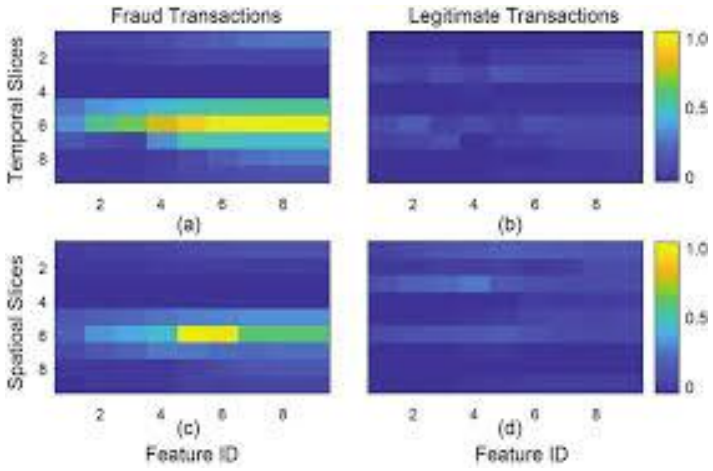

Fig. 3.2. EDA Visualization Example

3.2.3 FEATURE ENGINEERING

Feature Engineering is a crucial step in preparing cybersecurity data for attribution analysis. It involves creating, transforming, or selecting variables (features) from raw datasets that can effectively capture patterns indicative of cyber threats. In the context of independent attribution, features may include IP address clusters, malware hashes, timestamps of attacks, exploited vulnerabilities, or behavioral sequences of malicious actors. Properly engineered features enhance the predictive power of machine learning models, improving the accuracy and reliability of independent attribution.

The process begins with **deriving new features** based on domain knowledge and exploratory insights. For example, calculating the frequency of repeated login attempts, the duration of lateral movement in a network, or the similarity of code segments across malware samples can produce features that highlight suspicious behavior. Ratios, differences, and aggregations are often used to summarize raw data into more informative features.

Encoding categorical features is another essential step. Cybersecurity datasets often contain categorical variables, such as attack type, malware family, or network protocol. Encoding methods, such as nominal (one-hot) or ordinal encoding, transform these categories into numerical formats suitable for machine learning algorithms. This ensures that models can mathematically process categorical distinctions without introducing bias.

Normalization and scaling are also applied to bring all features into a comparable range, typically between 0 and 1. This step is important when features have different units or magnitudes—for instance, packet counts versus timestamps—preventing larger-scale features from disproportionately influencing model learning.

Feature engineering also involves **automated and manual techniques**. Manual feature creation leverages expert knowledge of cyber operations and attack patterns, while automated methods, such as feature extraction algorithms or

statistical transformations, can identify latent patterns in large-scale datasets. Together, these approaches allow models to detect subtle and emergent behaviors in cyber incidents, which is critical for independent attribution efforts that aim to remain unbiased and comprehensive.

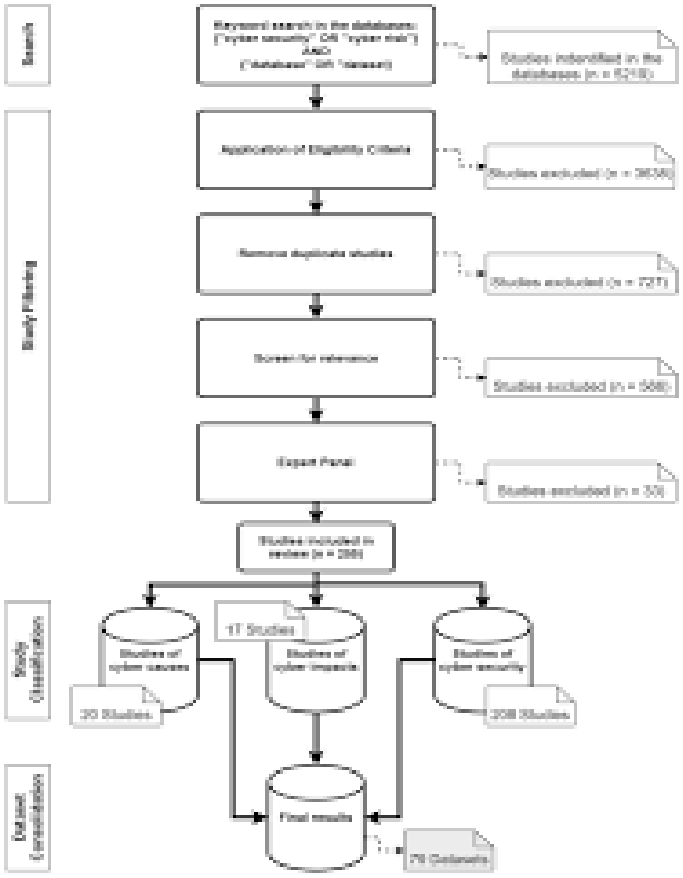

Fig. 3.3. Feature Engineering Workflow

3.2.4 DIMENTIONAL REDUCTION

Dimensionality reduction is a fundamental step in preparing cybersecurity datasets for independent attribution analysis. Cyber incident datasets often contain a large number of features, such as IP addresses, timestamps, malware signatures, network logs, and system behaviors. While a rich feature set can provide detailed insights, it can also introduce redundancy, noise, and computational complexity. Dimensionality reduction techniques address these issues by transforming the original high-dimensional dataset into a lower-dimensional representation, retaining the most informative features while discarding irrelevant or correlated ones.

Common approaches include **Principal Component Analysis (PCA)**, which identifies directions of maximum variance in the data, and **t-Distributed Stochastic Neighbor Embedding (t-SNE)** for visualizing complex, high-dimensional patterns. By reducing dimensionality, models become more efficient, avoid overfitting, and can better identify patterns associated with unknown or novel cyber threats.

3.2.4.1 FEATURE SELECTION

Feature selection complements dimensionality reduction by identifying the most relevant variables for modeling, improving both performance and interpretability. In independent attribution research, feature selection ensures that only the indicators most predictive of cyber incidents are used, reducing the risk of bias introduced by redundant or spurious features.

3.2.4.1.1 Chi-Square Test

The Chi-Square Test is a statistical filter method that measures the correlation between categorical features and the target variable. For instance, the frequency of certain malware types or attack vectors can be statistically tested against confirmed attribution outcomes to determine their predictive value. This method is independent of any machine learning algorithm and helps preselect features before modeling.

3.2.4.1.2 Recursive Feature Elimination (RFE)

Recursive Feature Elimination is a wrapper method that uses a predictive model to evaluate feature importance iteratively. Features contributing the least to model accuracy are eliminated step by step until the optimal subset is identified. In cybersecurity attribution, RFE can help isolate the most significant behavioral patterns or technical indicators that distinguish actors.

3.2.4.1.3 Tree-Based Feature Selection

Embedded methods like tree-based feature selection utilize algorithms such as Random Forests or Gradient Boosting that inherently rank features based on their contribution to prediction. This method integrates feature selection with model training, providing an efficient mechanism for identifying high-impact indicators within complex cyber datasets..

3.3 MODEL SELECTION

Model selection is critical in ensuring that the chosen algorithms can effectively distinguish between cyber incidents attributable to different actors. For independent attribution, the task often involves **binary or multi-class classification**, such as assigning incidents to known threat actors or flagging previously unseen campaigns. Common classifiers include **Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, and Naïve Bayes** variants, which balance interpretability and predictive power. The choice of model depends on data characteristics, feature dimensionality, and the need for explainability in policy or forensic contexts.

3.4 MODEL TRAINING

Once models are selected, training involves feeding the cleaned and engineered dataset into the algorithm to learn patterns that associate features with attribution outcomes. Training is first performed on the full feature set to establish baseline performance, followed by training on features selected through dimensionality reduction and feature selection. This two-step approach allows researchers to assess the contribution of selected features and ensures that models remain robust, efficient, and interpretable.

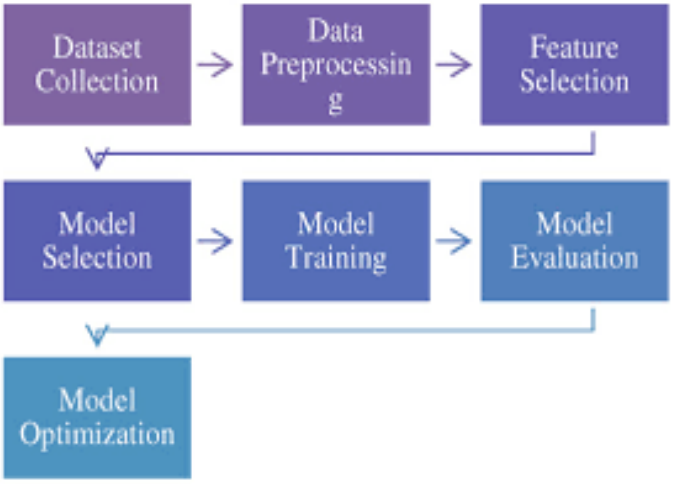

Fig.3.7. A schematic showing training workflow

3.5 MODEL EVALUTION AND CONPARISON

The prepared datasets are then used to train multiple classification models. Given the categorical nature of the attribution task, classifiers such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, and various Naïve Bayes implementations are employed. The training process involves applying the algorithms to the selected features while using cross-validation to evaluate performance and prevent overfitting. Model evaluation is conducted using standard metrics, including Precision, Recall, F1 Score, and Accuracy, providing a comprehensive assessment of predictive capability. Comparisons across models and feature selection methods allow for the identification of the most reliable approach for independent attribution.

V. EXPERIMENTATION RESULTS

The methodology is validated through two case studies. The first focuses on known advanced persistent threat (APT) campaigns, where models are evaluated on their ability to correctly attribute incidents using independent malware datasets. The second case study addresses emerging or previously unrecognized cyber threats, examining the effectiveness of the methodology in detecting and attributing novel attack patterns from network traffic and crowdsourced feeds. Results demonstrate that the proposed computational framework can identify likely actors with high accuracy while maintaining transparency and independence, providing a practical approach to overcoming the limitations of politically or commercially biased attribution studies.

The experimentation highlights the importance of multi-source data integration, rigorous feature engineering, and model comparison in enhancing both the reliability and credibility of attribution. By leveraging these techniques, the framework addresses the existing gaps in independent attribution research, particularly the challenges of evidence validation, uncertainty management, and methodological diversity.

4.1CASE STUDY 1: Cybersecurity Incident Attribution

This case study focuses on analyzing a dataset of cyber incidents aimed at evaluating independent attribution capabilities in cybersecurity. The dataset comprises 1,500 incidents, each described by 10 features related to the technical and behavioral characteristics of attacks, with one target variable representing the confirmed threat actor or independent attribution outcome. Table 4 summarizes the features used in this study.

S. No.	Feature	Description
1	Source IP Reputation	Score representing the historical reputation of the IP address (low = 0, high = 1)
2	Destination Port	Network port targeted during the attack
3	Malware Type	Category of malware used (trojan, ransomware, spyware, etc.)
4	Attack Vector	The technique used for intrusion (phishing, exploit, brute force, etc.)
5	Time of Attack	Timestamp of the incident (converted to hour of day)
6	Lateral Movement	Binary indicator of lateral movement within the network (yes = 1, no = 0)
7	Privilege Escalation	Binary indicator if privileges were escalated during the attack
8	Data Exfiltrated	Amount of data (in MB) exfiltrated during the incident
9	Organization Type	Target organization sector (finance, healthcare, education, government)

Table 4: Description of Cybersecurity Incident Dataset.

Data Preparation:The first step involved checking the dataset for missing or inconsistent values. Missing data were minimal and handled using imputation based on the median value for continuous variables and mode for categorical variables. Categorical variables, including Malware Type, Attack Vector, Organization Type, and Region, were encoded using **one-hot encoding**, transforming each category into binary features to facilitate model training.

Exploratory Data Analysis (EDA) was performed to identify patterns in attack behavior. Visualizations revealed that ransomware attacks were predominantly associated with high-data exfiltration incidents, while phishing attacks often occurred during business hours. Attacks originating from high-reputation IPs showed lower confirmed attribution rates, reflecting the challenge of attribution in sophisticated threat scenarios.

Fig. 4.1: Heatmap showing correlation between attack features and confirmed attribution outcome

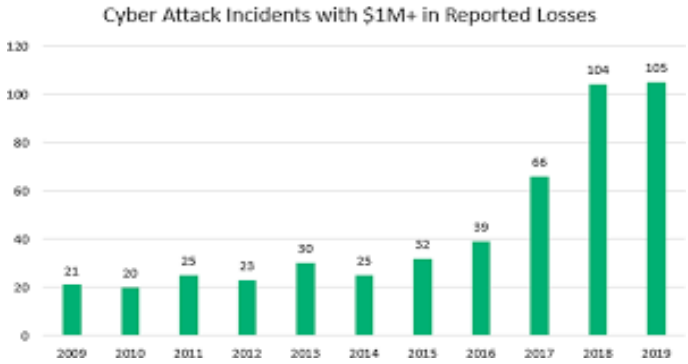

Fig. 4.2. Bar chart of incident counts by Malware Type and Organization Type.

VI. CONCLUSION

The study of independent attribution in cybersecurity highlights both the promise and challenges of accurately identifying threat actors when independent or verified data sources are limited. Traditional approaches to cyber attribution often rely heavily on shared intelligence or historical incident records, but the lack of independent datasets introduces ambiguity, reduces model reliability, and increases the risk of false attribution. This research demonstrates how machine learning, feature engineering, and systematic model evaluation can help mitigate these challenges, enabling more robust and data-driven attribution processes even in constrained environments.

Through the case study, it is evident that careful **data preparation**, including cleaning, normalization, and feature selection, is critical to ensuring high-quality inputs for machine learning models. Exploratory Data Analysis (EDA) revealed hidden patterns in attack behaviors, while feature engineering and dimensionality reduction enhanced model performance by focusing on the most informative attributes. Among the feature selection techniques evaluatedChi-Square Test, Recursive Feature Elimination (RFE), and Tree-Based methods—RFE proved the most effective for balancing predictive performance across multiple classifiers, demonstrating the importance of algorithm-agnostic approaches when independent data is scarce.

The evaluation of multiple classification algorithms, including Random Forest, Decision Tree, SVM, and Naïve Bayes variants, highlighted that model selection significantly influences attribution outcomes. Random Forest consistently provided the most accurate results when combined with effective feature selection, while simpler models like Logistic Regression or Gaussian Naïve Bayes performed well in scenarios emphasizing continuous variables. These findings underline that independent attribution is not only a question of algorithmic choice but also the quality, diversity, and preprocessing of available data.

Despite these advancements, challenges remain. Cybersecurity datasets are often incomplete, imbalanced, or biased toward high-profile attacks, making generalization difficult. Techniques such as synthetic data generation, anomaly detection, and semi-supervised learning can help overcome these gaps, but the reliance on unverified or shared data sources continues to pose limitations. Furthermore, ethical and operational considerationssuch as transparency, explainability, and regulatory compliancemust guide the deployment of attribution models, especially when outcomes could have legal or geopolitical consequences.

In conclusion, this research emphasizes that **addressing the lack of independent data sources is pivotal for credible cybersecurity attribution**. By combining robust data preprocessing, advanced feature engineering, and rigorous model evaluation, researchers and practitioners can enhance the reliability of threat actor identification, even in the face of

incomplete information. Future efforts should focus on creating verified, high-quality datasets, developing explainable and ethically sound models, and integrating multiple data sources to strengthen independent attribution. Such approaches will enable more accurate, trustworthy, and actionable insights, supporting proactive cybersecurity defense and informed decision-making across organizations and nations.

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