Threat Assessment in Machine Learning based Systems

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Abstract—Machine learning is a field of artificial intelligence (AI) that is becoming essential for several critical systems, making it a good target for threat actors. Threat actors exploit different Tactics, Techniques, and Procedures (TTPs) against the confidentiality, integrity, and availability of Machine Learning (ML) systems. During the ML cycle, they exploit adversarial TTPs to poison data and fool ML-based systems. In recent years, multiple security practices have been proposed for traditional systems but they are not enough to cope with the nature of ML-based systems. In this paper, we conduct an empirical study of threats reported against ML-based systems with the aim to understand and characterize the nature of ML threats and identify common mitigation strategies. The study is based on 89 real-world ML attack scenarios from the MITRE’s ATLAS database, the AI Incident Database, and the literature; 854 ML repositories from the GitHub search and the Python Packaging Advisory database, selected based on their reputation. Attacks from the AI Incident Database and the literature are used to identify vulnerabilities and new types of threats that were not documented in ATLAS. Results show that convolutional neural networks were one of the most targeted models among the attack scenarios. ML repositories with the largest vulnerability prominence include TensorFlow, OpenCV, and Notebook. In this paper, we also report the most frequent vulnerabilities in the studied ML repositories, the most targeted ML phases and models, the most used TTPs in ML phases and attack scenarios. This information is particularly important for red/blue teams to better conduct attacks/defenses, for practitioners to prevent threats during ML development, and for researchers to develop efficient defense mechanisms.

Index Terms—Machine Learning, Vulnerabilities, Threat Assessment, TTP, Computer security, Artificial Intelligence.

1 INTRODUCTION

Nowadays, Machine Learning (ML) is achieving significant success in dealing with various complex problems in safety-critical domains such as healthcare [1] and space [2]. ML has also been applied in cybersecurity to detect threatening anomalous behaviors such as spams, malwares, and malicious URLs [3], allowing a system to respond to real-time inputs, containing both normal and suspicious data, and learn to reject malicious behavior. While ML is strengthening defense systems, it also helps threat actors to improve their tactics, techniques, and procedures (TTPs), and expand their attack surface. Attackers leverage the black-box nature of ML models and manipulate input data to affect their performance [4–7].

Most recent work [4], [6–14] outlined ML attacks and defenses targeting different phases of the ML lifecycle, i.e., input data, training, inference, and monitoring. ML-based systems are also often deployed on-premise or on cloud service providers; which increases attack vectors and makes them vulnerable to traditional attacks at different layers: software-level, system-level, and network-level. At the software-level, ML-based systems are vulnerable to operating system (OS) attacks since attackers can exploit OS vulnerabilities and bugs to break it. At the system-level, ML-based systems are vulnerable to several attacks, including CPU side-channel [15] and memory-based [16] attacks. At the network-level, ML-based systems can be compromised under several attacks [3], including Denial of Service (DoS), botnets, and ransomwares. To achieve their goals, ML threat actors can poison data and fool ML-based systems using evasion [6], [7], [9], [13], extraction [4], [17], [18], inference [7], [19], and poisoning [4–7], [9], [13]. To defend against such threats, adversarial defenses have been proposed including [8], [11]. Usually, threat TTPs and mitigations are reported in a threat assessment framework to help conduct attack and defense operations. Unfortunately, there is lacking concrete applications of threat assessment in the ML field that provide a broader overview of ML threats, ML tool vulnerabilities, and mitigation solutions.

Contributions. In this work, our goal is to contribute to ML threat assessment by leveraging existing standard frameworks [20], [21] containing knowledge of TTPs as well as the vulnerabilities reported in ML repositories. The contributions in this paper include:

- new threat TTPs extracted from the AI Incident database [22] and the literature to complete the MITRE’s ATLAS database;
- the mapping of threat TTPs from multiple databases to ML phases, models, and tools to evaluate threat impact on ML components;
- a vulnerability analysis of ML repositories as well as the dependencies that cause them to foresee potential threats in the use of a particular ML library;
- a multi-layer ML mitigation matrix that leverages security guidance from standard databases [20], [23–25], National Institute of Standards and Technology (NIST), and Cloud Security Alliance to help prevent, detect, and respond against ML threats.

To achieve this goal, we conduct an empirical study to characterize ML threats, understand their impacts on ML
2 BACKGROUND AND RELATED WORK

Before diving in ML threat assessment, generic security concepts such as assets, vulnerabilities, and threats must be defined. This section provides an overview of security concepts and related work.

components (i.e., phases, models, tools), and identify common mitigation strategies. Results show that deep neural networks (DNNs) such as convolutional neural networks (CNNs) are one of the most targeted models in attack scenarios. ML repositories such as TensorFlow, OpenCV, and Notebook, Numpy have the largest vulnerability prominence. The most severe dependencies that caused the vulnerabilities include pickle, joblib, numpy116, python3.9.1, and log4j. DoS and buffer-overflow were the most frequent in ML repositories. Our examinations of vulnerabilities and attacks reveal that testing, inference, training, and data collection are the most targeted ML phases by threat actors. The mitigations of these vulnerabilities and threats include adversarial defenses [8], [11], [25] and traditional defenses such as software updates, and cloud security policies (e.g., zero trust). Leveraging our findings, ML read/blue teams can take advantage of the ATLAS TTPs and the newly-identified TTPs from the AI incident database to better conduct attacks/defenses using the most exploited TTPs and models for more impact. Since ML-based systems are increasingly in production, ML practitioners can leverage these results to prevent vulnerabilities and threats in ML products during their lifecycle. Researchers can also use the results to propose theories and algorithms for strengthening defenses.

The rest of this paper is structured as follows. In Section 2 we define basic concepts such as vulnerabilities, threats; and review the related literature. Section 3 describes the study methodology for threat assessment while defining some research questions and presents a formal definition of an ML threat. In Section 4 we present results while answering to the defined research questions. Section 5 proposes mitigation solutions for the observed threats and vulnerabilities. Section 6 discusses threats that could affect the validity of the reported results. Section 7 concludes the paper and outlines avenues for future work.

2.1 Assets

In computer security, an asset is any valuable logical or physical object owned by the organization such as data, database, software, hardware, storage, and network devices (see Fig 1). At data level, ML assets can be access keys (tokens, user/password, private/public key, certificates), datasets, models and their parameters, source code, and libraries. At software level, ML assets can be model as a service (MaaS) APIs, ML apps in production, containers and virtual machines (VMs) where ML apps are deployed. At storage level, ML assets can databases, objects (e.g., buckets), files, and blocks to host ML training datasets, models, and code. At system level, ML assets can be servers, racks, data centers, and clusters. At network level, ML assets can be firewalls, routers, gateways, switches, and load balancers.

2.2 Vulnerabilities

A vulnerability is a software or hardware flaw that can be exploited by threat actors to execute malicious command and control (C2) operations such as data theft and destruction.

Types of vulnerabilities

Vulnerabilities occur at different levels: data, software, storage, system, and network (see Fig 1). At the data level, data assets are vulnerable to model stealing, backdooring [27], poisoning, injection, evasion, and inference. At the software level, threat actors look at errors or bugs in ML apps such as buffer overflow, exposed credentials, and security misconfigurations. At the storage level, ML databases and cloud storage are vulnerable to weak authentication, improper backup, and SQL injection attacks. At system level, they exploit several hardware vulnerabilities including firmware unpatching and CPU side-channel [15] to launch attacks such as DoS, affecting the ML cloud infrastructure where ML apps are managed. At network level, threat actors can exploit improper configurations of the network making it vulnerable to distributed DoS and botnet attacks. These vulnerabilities are reported in Common Weaknesses Exposure (CWE) Top 25, OWASP Top 10, National Vulnerability Database (NVD), and Common Vulnerability and Exposures (CVE) standards.
2.3 Threats

A threat exploits a given vulnerability to damage and/or destroy a target asset. Threats can be of two types: insider threats and outsider threats. Insider threats originate from the internal system and they are more often executed by a trusted entity of the system (e.g., employee). Outsider threats are operated from the remote/external system. In the following, we distinguish between traditional threats and recent machine learning threats.

Traditional threats

Adversarial Tactics, Techniques, and Common Knowledge (ATT&CK) [23] is a public and standard knowledge database of attack TTPs. Traditional attack phases are divided into two groups: traditional pre-attack phases and attack phases.

Pre-attack: The pre-attack phase consists of two tactics: reconnaissance and resource development [23]. During reconnaissance, attackers use several techniques including network scanning to find information about a victim such as open ports and OS version (e.g., nmap, censys), and use phishing techniques to embed malicious links in emails or SMS messages. During resource development, attackers use several techniques including acquisition of resources to support C2 operations (e.g., domains), purchasing a network of compromised systems (botnet) for C2, development of tools (e.g., crawlers, exploit toolkits), and phishing.

Attack: Once the pre-attack phase is done, attackers will attempt an initial access to the target victim host or network by delivering a malicious file or links through phishing; exploiting vulnerabilities in websites/softwares used by victims; and manipulating software dependencies and development tools prior to their delivery to the final consumer. Upon the success of the initial access, they will execute malicious code on the victim host/network. After execution, they will attempt to persist on the target by modifying registries (e.g., Run Keys/Startup Folder), and automatically executing at boot. In addition, attackers will try to gain high-level permissions (e.g., as root/administrator). To hide their bad actions, they will make sure they are undetected by installed antivirus or Endpoint Detection Response (EDR) tools. An attacker can also execute lateral movement techniques such as exploitation of remote services to spread on other hosts or networks for impact.

Machine learning threats

Adversarial Threat Landscape for Artificial Intelligence Systems (ATLAS) [20] is a public and standard knowledge database of adversarial TTPs for ML-based systems [20]. ML attack phases are divided into two groups: ML pre-attack phases and attack phases.

ML Pre-attack: ML pre-attack tactics are similar to the one used in traditional threats, but with new techniques and procedures adapted to the ML context [20]. During reconnaissance, Threat actors will search for victim’s publicly available research materials such as technical blogs, and pre-print repositories; and search for public ML artifacts such as development tools (e.g., TensorFlow). For resource development, they will also acquire adversarial ML attack implementations such as adversarial robustness toolbox (ART).

ML Attack: ML systems are vulnerable to traditional attacks and another kind of attacks that turns their normal behaviors into threatening behaviors called adversarial attacks. Like traditional threats, ML threats target confidentiality, integrity, and availability of data. To achieve the goal, attackers may have full knowledge (white-box), partial knowledge (gray-box), or no knowledge (black-box) of the targeted ML system. In black-box settings, attackers do not have access to the training dataset, model, and the executing code (since assets are hosted in a private corporate network) but they have an access to the public ML API as a legitimated user. This allows them to only perform queries and observe outputs [30].

In white-box settings, attackers have a knowledge of the model architecture and can access the training dataset or model to manipulate the training process. In gray-box settings, they have either a partial knowledge of the model architecture or some information about the training process. Whether white-box, gray-box or black attacks, they can be focused on a particular class/sample (targeted) or any class/sample with no specific choice (untargeted) to cause models misclassify inputs. Different techniques are used for attacks: poisoning, evasion, extraction, and inference. During poisoning [5], [6], [9], [13], [14], [31]–[33], attackers injects false training data to corrupt the learning model (even allowing it to be backdoored [27]) to in order to achieve an expected goal at inference time. During evasion [6], [10], [34], [35], attackers iteratively and carefully modify ML API queries and observing the output at inference time [30]. The queries seem normal but are misclassified by ML models. During extraction [4], [17], [18], [36], attackers iteratively query the online model [30] allowing them to extract information about the model. Then, they use this information to gradually train a substitute model that imitates the predictive behaviour of the target model. During inference [19], [37], [38], attackers probe the online model with different queries. Based on the results, they can infer whether features are used to train the model or not; allowing them to compromise private data.

The adversarial models used [7] for attack include (1) fast gradient sign method (FGSM) which consists in adding noise with the same direction as the gradient of the cost function w.r.t to data, (2) DeepFool efficiently computes perturbations that fool deep networks, (3) Carlini and Wagner (CW) is a set of three attacks against defensive distilled neural networks [39], (4) Jacobian-based saliency map (JSMA) saturates a few pixels in an image to their maximum/minimum values, (5) universal adversarial perturbations are agnostic-image perturbations that can fool a network on any image with high probability, (6) Basic Iterative Method (BIM) is an iterative version of the FGSM, (7) one pixel is when a single pixel in the image is changed to fool classifiers, (8) Iterative Least-Likely Class Method (ILCM) is an extension of BIM where an image label is replaced by a target label of the least-likely class predicted by a classifier, and (9) Adversarial Transformation Networks (ATNs) turns any input into an adversarial attack on the target network, while disrupting the original inputs and outputs of the target network as little as possible.
2.4 Related work

In computer security, threat assessment is a continuous process that consists in identifying, analyzing, evaluating, and mitigating threats. It has been applied for assessing threats in traditional systems [40] but to date, there are no concrete applications of this process for ML-based systems. The ATLAS framework is the first thorough real-world attempt of ML threat assessment built by the MITRE Corporation jointly with some organisations including Microsoft and Palo Alto Networks [20]. Most recent work used ATT&CK for threat assessment. Kumar et al. [41] identified gaps during ML development, deployment, and when ML-based system is under attack. Then, they enumerated ML security aspects (e.g., static/dynamic analysis of ML systems, auditing and logging) to be considered in industry. The mitigations proposed in this paper include ML security aspects by Kumar et al. with additional security aspects in standards (ATT&CK mitigations, Cloud Security Alliance, NIST), and we better organize it in terms of layer (data level to cloud level, assets, and ML pipelines) and in terms of course of action (i.e., harden, detect, isolate, evict) following MITRE D3FEND [24]. Lakhdhar et al. [42] mapped new discovered vulnerabilities to potential attack tactics in ATT&CK by extracting features (e.g., CVSS severity score, vendor) to train a RandomForest-based model. This approach is limited to the ATT&CK database and maps only vulnerabilities to ATT&CK TTPs. Kuppa et al. [43] also mapped CVE’s to ATT&CK techniques using a multi-head joint embedding neural network, trained using threat reports from Symantec and Google Project Zero. Like [42], this approach is limited to the ATT&CK database and maps only vulnerabilities to ATT&CK TTPs.

Our threat assessment leverages ATLAS, ATT&CK and other databases like the AI Incident Database [22] to have a complete set of TTP definitions for ML threat characterization, ML phase and model mapping. The threat assessment process is also coupled with a vulnerability assessment that identifies, analyzes, evaluates, and mitigates vulnerabilities in ML-based systems. In addition, it leverages defenses frameworks (ATT&CK mitigations [44], D3FEND [24]), Cloud Security Alliance [45] and NIST security guidelines [46]-[52] to provide mitigations during the ML lifecycle. This combination provides a complete and broader end-to-end threat assessment of ML assets. In the following section, we show how ATLAS TTPs affect ML components at different phases of the ML lifecycle and how traditional threats/vulnerabilities affect ML repositories.

3 STUDY METHODOLOGY

The goal of this study is to analyze ML threat behaviors (i.e., common entry points, prominent threat tactics, common TTP stages) and understand their impact on ML components (i.e., vulnerable ML phases, models, tools and, related-dependencies) by leveraging ML threat knowledge in ATLAS, ATT&CK and the AI Incident Database as well as vulnerabilities from ML repositories to foresee potential threats in the use of a particular package or library. The perspective of this study is that of ML red/blue teams, researchers, and practitioners looking to gain knowledge about ML threat TTPs, prevent and defend against those threats, build, and deploy secure ML products from staging to production environment. The context of this study consists of 89 real-world ML attack scenarios (15 from ATLAS,
60 from the AI Incident Database, 13 from the literature) and 854 ML repositories (845 from GitHub, 9 from PyPA [53]). In Fig. 2 the road map of the study is shown. To achieve our goal, we address the following research questions:

**RQ1:** What are the prominence and common entry points of threat TTPs exploited in ML attack scenarios? This research question aims to gain knowledge about ML threat TTPs in order to allow the implementation of better defenses strategies. In this question, we also examine the execution flows of ML attack scenarios to identify the most used TTPs and TTP sequences adopted by attack scenarios, in order to defend against them.

**RQ2:** What is the effect of threat TTPs on different ML phases and ML models? This research question aims to understand the effect of each threat tactic identified in RQ1 on ML phases and ML models, with the aim to help secure each component of the ML lifecycle. Through this research question, we also aim to identify the most targeted ML phases as well as the most used threat TTPs in the different ML phases.

**RQ3:** Are there new real-world threats in the AI Incident Database, the literature, and ML repositories that were not documented in the ATLAS database? This research question aims to assess the completeness of ATLAS with the aim to identify other security threats that may have been overlooked as well as the most vulnerable ML repositories, the dependencies that cause them, and the most frequent vulnerabilities in the ML repositories.

**RQ4:** How can ML stakeholders harden their ML assets and prevent ML threats during development to production stage from data level to cloud level? This research question aims to provide end-to-end mitigation solutions to ensure security of ML assets based on [20, 23, 24, 45].

### 3.1 Threat Model

**Goal.** Attackers aim to affect the confidentiality, integrity, and availability of data (e.g., training data, features, model) depending on threat objectives. Poisoning attacks can affect data integrity. Extraction attacks can allow one to steal models or features; thus affecting confidentiality.

Let \( a \in A \) be an asset, where \( A \) is a set of assets from the system \( S \). An asset \( a \) can be owned or accessed by an entity (e.g., user, user group, program, set of program), denoted \( E \). \( E \) denotes the set of all entities and \( E \in E \). Let \( AC_S : A \times E \to R \) be a function, that defines the level of privilege that an entity \( E \) has on an asset \( a \) or an asset group \( A_a \subseteq A \), under the system \( S \). \( R \) is a set of right access and it can take values (1) \( R = \{ \text{none}, \text{user}, \text{root} \} \) meaning that entities can have either no privilege (none), user access on \( A \) (user), and full access on \( A \) (root); or (2) \( R = \{ \text{none}, \text{read}, \text{write} \} \) meaning that entities can have no privilege (none), read access on \( A \) (read), and write access on \( A \) (write). When \( AC_{AWS}(\text{model.pkl}\_ml\_api) = \text{root} \), it means that the Amazon Web Service (AWS) ML API service \( ml\_api \) have full access on the pickled model file \( \text{model.pkl} \). When \( AC_{VM}(\text{training.csv}'\_john') = \text{write} \), it means that user \( john \) can modify or delete the training data file \( \text{training.csv} \) in the virtual machine \( VM \).

Let \( P_1, ... P_n \) be a set of premises and \( C \) the goal to achieve. This relation is represented by

\[
P_1, ... P_n \models C
\]

It also means that \( C \) can succeed when properties \( P_1, ... P_n \) are satisfied. Based on [54], we define the following notations

\[
\models a \models E
\]

means that \( a \) is \( E \)’s asset. Given \( k_E \in K \) a protection property (e.g., encryption key, certificate, token), the notation

\[
\{a\}_k_E
\]

means that the protection \( k_E \) is enforced on asset \( a \) by an entity \( E \). Let \( E_1, E_2 \in E \) be two entities that share an asset \( a \). The notation

\[
E_1 \leftrightarrow E_2
\]

means that \( a \) is shared by \( E_1 \) and \( E_2 \). The sharing is satisfied when \( E_1 \) send \( a \) to \( E_2 \) and \( E_2 \) send \( a \) to \( E_1 \) as follows,

\[
E_1 \models E_2, E_2 \models E_1
\]

Let \( m : A \to C \) be a model function that takes data in \( A \) and return decisions in \( C \) based on the inputs. \( C \) can be two classes (i.e., \( \{c_1, c_2\} \) or multiple classes (i.e., \( \{c_1, c_2, ..., c_n\} \)), where \( c_1, c_2, ..., c_n \in C \).

**Knowledge.** In black-box settings, an attacker \( AT \) does not have direct access [30] to ML assets \( A_V \) of the target victim \( V \) (i.e., model, executing code, datasets), i.e., \( \forall a_V \in A_V, AC_V(a_V, AT) = \text{none} \). They have only access to the ML inference API using an access token \( k_V \) obtained as a legitimate user from the victim’s platform \( V \), i.e.,

\[
\xrightarrow{\{a_{AT}\}_k_V} V
\]

where \( a_{AT} \in A \) are data crafted offline by attacker \( AT \) to be send via API. During the attack, \( AT \) performs queries using the victim’s ML inference API and observe outputs. To do so, \( AT \) sends an online request with the crafted data \( a_{AT} \) using access token \( k_V \), i.e.,

\[
AT \xrightarrow{\{a_{AT}\}_k_V} V
\]

Then, \( AT \) will receive prediction responses and analyze it to further improve its data for attack, i.e.,

\[
V \xrightarrow{mv(a_{ AT})} AT
\]

where \( mv \) is the executed model behind the ML inference API of the target victim \( V \).

In white-box settings, attacker \( AT \) may have an internal access to some ML assets \( A_V \subseteq A_V \) of the target victim \( V \) (e.g., model, training data), i.e.,

\[
\forall a_V \in \hat{A}_V, AC_V(a_V, AT) \in \{\text{read, write}\}
\]
Then, $AT$ can perform several state-of-the-art attack techniques such as poisoning, evasion, extraction, and inference (see Section 2.3).

**Specificity.** In adversarial settings, ML threats can target a specific class/sample for misclassification (adversarily targeted) or any class/sample for misclassification (adversarially untargeted). The goal of $AT$ is to maximize the loss $L$ so that model $m_{V}$ misclassifies input data,

$$
\arg \max_{a} L(m_{V}(a), c)
$$

where $a \in A$ is an input data, and $c \in C$ is a target class, and $m_{V}(a)$ is the predicted target data given $a$. To achieve the goal, $AT$ can execute a targeted or untargeted attack affecting integrity and confidentiality of data [5], [55].

When attack is targeted, $AT$ substitutes the predicted class $c$ by adding a small perturbation $\theta_{a}(a, c)$ so that

$$
m_{V}(a_{AT}) = c
$$

where $a_{AT} = a + \theta_{a}(a, c)$ is an adversarial sample.

In untargeted attack, $AT$ adds a small perturbation $\theta_{i}(a)$ to input $a$ so that

$$
m_{V}(a_{AT}) \neq m_{V}(a)
$$

where $a_{AT} = a + \theta_{i}(a)$ is an adversarial sample. ML threats can also leverage traditional TTPs to achieve goal.

In traditional settings, threat actors can actively pursue and compromise the target system while maintaining anonymity (traditionally targeted) or can simply spread on the network as possible without a particular target (traditionally targeted). Terms Adversarially (resp. Traditionally) are used to distinguish the attack specificity in adversarial settings (resp. traditional settings). In traditional attacks, $AT$ targets assets such as user accounts, servers, virtual machines, databases, and networks by bypassing authentication and firewalls. This allows him to get full control of the ML assets of $V$, i.e., $\forall a_{V} \in A_{V}, AC_{V}(a_{V}, AT) = root$ and cause more damages.

**Capability.** To launch ML attacks, threat actors use the following tactics [20]: Reconnaissance, Resource Development, Initial Access, ML Model Access, Execution, Persistence, Defense Evasion, Discovery, Collection, ML attack staging, Exfiltration, and Impact. During Reconnaissance and Resource Development, attackers gather information (e.g., papers, repositories) and setup C2 infrastructure to start the attack. During initial access, they try to gain access to the victim infrastructure containing ML artifacts. Then, they try to gain access to the internals of the model and the physical environment (ML Model Access). Attackers can also run remote-controlled malicious code to steal data (Execution). To persist on the ML system, they can use backdoored ML models or keep access to the target (Persistence). Attackers also leverage evasion tactics [6], [10], [34], [35] to bypass classifiers (Evasion). When attack succeeded, they can collect data for exfiltration. During attack staging, they can train proxy models, craft adversarial data, and poison the target model for impact (e.g., human loss, ML system destruction).

### 3.2 Data collection

To select data sources, we define three criteria: more recent data, consistency, and reputation. The first criteria ensures that data sources contain recent information about ML vulnerabilities and threats. The ATLAS database has been selected since it is recent, i.e., containing threats from 2019 to 2021 [20]. The well-known ATT&CK database also contains enterprise attacks from 2018 to 2021 and it is used to complete TTP definitions in ATLAS; since some attack scenarios employed both tactics from ATLAS and ATT&CK. In addition, the AI Incident database contains recent real-world AI incident information from 2003 to 2022 [22]. Consistency criteria checks whether data sources have a significant amount of vulnerability or threat information. ATLAS contains 15 ML attack scenarios, 12 tactics, and 30 techniques with 43 sub-techniques [20]. Since ATLAS is not consistent, 60 real-world threats are collected from the AI Incident database [22] between 2018 to 2022 and 14 threats from the literature between 2010 to 2021. Similar to ATLAS, ATT&CK contains 14 enterprise tactics and 188 enterprise techniques with 379 sub-techniques [21]. Reputation criteria selects the best data sources based on the reputation of the maintaining organizations, the number of stars for GitHub repositories, and the frequency of updates. ATLAS and ATT&CK are maintained by top organisations such as the MITRE corporation, Microsoft, McAfee, Palo Alto Networks, IBM, and NVIDIA. The AI Incident Database contains real-world attack information from top medias such as Forbes, BBC, New York Times, and CNN. Most papers [4], [17], [31], [33], [34], [37], [55]–[62] selected in the literature are also well-known in the ML community.

ML repositories from the GitHub search are also selected using the reputation criteria such as the number of stars and the notoriety of the maintaining organizations. To select reputed repositories, we search Github code search API using the following query: `machine-learning in:topic stars:>`.

### 3.3 Data processing

Data processing consists in three phases: extraction, correlation, and metric computation. Threat information is extracted manually from the ATLAS database and the literature by reading ML attack scenarios, looking at the tactics used, and finding the tactic descriptions referred in ATLAS or ATT&CK. The AI Incident database has been also scrutinized to get recent ML real-world attacks using a crawler [64] and keywords such as `attack`. Next, vulnerability and threat information is extracted from ML.
Fig. 3: TTP definitions for Microsoft-Azure service attack

### 3.3.1 Data extraction

We extract data from the ATLAS database, the AI Incident database, the literature, and ML repositories. **ATLAS database.** We extract all the 15 ML attack scenarios provided as well as their TTP definitions referred in ATLAS (12 tactics, 30 techniques, 43 sub-techniques) and ATT&CK (14 enterprise tactics, 188 enterprise techniques, 379 sub-techniques) by reading the description of each ML attack scenario, finding ATLAS and ATT&CK descriptions of the tactics used during the stages of the ML attack scenario. We also extract the attack goal, knowledge, and specificity for each attack scenario following the threat model (see Section 3.4.1). In [65], an attack scenario is decomposed into phases which are further decomposed into steps following ML attack phases described in the threat model. Each attack phase represents a tactic and the associated execution steps are techniques.

An attack scenario is illustrated in Fig. 3. The attack called **Microsoft-Azure service** [65] was executed by the Microsoft Azure Red Team and Azure Trustworthy ML Team against the Azure ML service in production. It has 6 phases. In Phase 1, they collected information necessary for the attack such as Microsoft publications on ML model architectures and open source models. Next, the team used valid accounts to access the internal network (Phase 2). Then, they found training data and model file of the target ML model that allowed them to execute further ML attack stages (Phase 3). During ML attack staging, they crafted adversarial data using target data and model (Phase 4). In Phase 5, they exploited an exposed inference API to gain legitimate access to the Azure ML service. Then, they successfully executed crafted adversarial data on the online ML service. This attack targets the confidentiality (unauthorized access to the Azure ML service) of the ML system. The attack knowledge is white-box since attackers have full access to the training data and the model. The attack goal is to cause the ML model to misclassify inputs.

| Tactic: Reconnaissance |
|------------------------|
| Technique: Search for Victim’s Publicly Available Research Materials |

| Tactic: Initial Access |
|-----------------------|
| Technique: Valid Accounts |

| Tactic: Collection |
|--------------------|
| Technique: ML Artifact Collection |

| Tactic: ML Attack Staging |
|---------------------------|
| Technique: White-Box Optimization |

| Tactic: ML Model Access |
|-------------------------|
| Technique: ML Model Inference API Access |

| Tactic: Impact |
|---------------|
| Technique: Evade ML Model |

### References

1. [65] was executed by the Microsoft Azure Red Team and Azure Trustworthy ML Team against the Azure ML service in production. It has 6 phases. In Phase 1, they collected information necessary for the attack such as Microsoft publications on ML model architectures and open source models. Next, the team used valid accounts to access the internal network (Phase 2). Then, they found training data and model file of the target ML model that allowed them to execute further ML attack stages (Phase 3). During ML attack staging, they crafted adversarial data using target data and model (Phase 4). In Phase 5, they exploited an exposed inference API to gain legitimate access to the Azure ML service. Then, they successfully executed crafted adversarial data on the online ML service. This attack targets the confidentiality (unauthorized access to the Azure ML service) of the ML system. The attack knowledge is white-box since attackers have full access to the training data and the model. The attack goal is to cause the ML model to misclassify inputs.

**AI Incident database.** We automatically extract 64 recent ML real-world attacks using query **attack** and the period between 2018 and 2022 using a crawler [64]. Then, we remove row duplicates and it remains 60 ML real-world attacks. Then, we manually read the description of these attacks using the reference link to identify if there are potential TTPs similar to those in ATLAS/ATT&CK.
and explicit mention of the models used, the attack goal, the attack knowledge and specificity. A sample of the extracted attacks (title, description, date, references) is shown in Table 1. The remainder can be found in the replication package [64]. Among the 60 new threats [64], only 13 ML threats have some threat tactics/techniques mentioned in ATLAS/ATT&CK. Some records have different names but was similar; thus we have considered 8 unique records. Table 2 shows a description of the new TTPs extracted in ML threats in the form atlas_tactic (atlas_tech1, atlas_tech2,...), where atlas_tactic (resp. atlas_tech) is an ATLAS tactic (resp. technique). These 8 ML real-world attacks were not documented in ATLAS and are used to complete case studies in the ATLAS database.

Fig. 4: TTP definitions for new Indian Tek Fog Shrouds an Escalating Political War attack

In Table 2 let consider the ML real-world attack Indian Tek Fog Shrouds an Escalating Political War. Following the reference link in Table 1 Tek Fog is an ML-based bot app used to distort public opinion by creating temporary email addresses and bypassing authentication systems (i.e., WhatsApp, Facebook, Instagram, Twitter and Telegram) to send fake news, automatically hijacking Twitter and Facebook trends such as retweeting/sharing posts to amplify propaganda, phishing inactive WhatsApp accounts and spying personal information (e.g., phone number, contact list), and building a database of citizens for harassment. The bot may uses Transformer model such as GPT-2 to generate coherent text-like messages [69]. This allows to deduce the 4 following ML TTPs (see Fig. 3): Resource Development (Establish Accounts), Initial Access (Valid Accounts), ML Attack Staging (Create Proxy ML Model: Use Pre-Trained Model), and Exfiltration (Exfiltration via Cyber Means). This attack targets the confidentiality (bypass authentication systems, spy personal information) and integrity (post fake news about the victim) of the ML system. The attack specificity is traditionally targeted; since threat actors target specific inactive WhatsApp accounts to spy personal information. There is no detail about the attack knowledge in the adversarial context.

Literature. We have manually extracted TTPs in the 14 papers by reading the attack information (i.e., technique/tactic, goal, knowledge, specificity) and linking them with TTP definitions in ATLAS and ATT&CK. Table 3 shows a description of the ML threats extracted and their TTPs in the form atlas_tactic(atlas_tech1, atlas_tech2,...), where atlas_tactic (resp. atlas_tech) is an ATLAS tactic (resp. technique).

In Table 3 let consider the Carlini et al. [4] attack. The attack uses the GPT-2 pre-trained proxy model and then steals/extracts training examples by querying the target model. We can deduce two TTPs: ML Attack Staging (Create Proxy ML model: Use Pre-Trained Model), and Exfiltration (Exfiltration via ML Inference API: Extract ML Model) and Exfiltration (Exfiltration via ML Inference API: Infer Training Data Membership).

GitHub. We have mined titles and comments from issues in the 845 ML repositories and automatically extracted relevant vulnerability and threat information using two filters. The first one is the comment filter which is a disjunction OR of the GitHub search pattern (keyword) in:comments, where (keyword) are query keywords such as cve for CVE code, vuln for vulnerability, threat for threat, attack for attack and attacker, secure for secure and security. These signatures are commonly used by cybersecurity teams to describe potential

| Title | Tactics and Techniques |
|-------|------------------------|
| Carlini et al. [4] | ML Attack Staging (Create Proxy ML model: Use Pre-Trained Model), Exfiltration (Exfiltration via ML Inference API: Extract ML Model) |
| Biggio et al. [54] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Barreno et al. [55] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Carlini et al. [56] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Wallace et al. [57] | ML Attack Staging (Create Proxy ML model: Use Pre-Trained Model), Exfiltration (Exfiltration via ML Inference API: Extract ML Model) |
| Abdullah et al. [53] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Chen et al. [51] | ML Attack Staging (Craft Adversarial Data: Insert Backdoor Trigger), Persistence (Backdoor ML Model: Inject Payload) |
| Choquette-Choo et al. [37] | ML Attack Staging (Craft Adversarial Data), Exfiltration (Exfiltration via ML Inference API: Infer Training Data Membership) |
| Papernot et al. [58] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Goodfellow et al. [59] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Papernot et al. [60] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Case et al. [61] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Athalye et al. [62] | ML Attack Staging (Craft Adversarial Data), Defense Evasion (Evade ML Model), Impact (Evade ML Model) |
| Jagielski et al. [17] | Reconnaissance (Search for Victim’s Publicly Available Research Materials), ML Attack Staging (Craft Adversarial Data), Exfiltration (Exfiltration via ML Inference API: Extract ML Model) |
security issues, threats, or vulnerabilities. The next one is title filter where in:comments is just replaced by in:title [64]. For example, Table 4 shows a sample of comments and titles from a filtered repository (i.e., TensorFlow) containing keyword vuln highlighted in green color. After filtering, it remained 34 repositories described in the repository package [64]. 23 repositories contained no relevant information (e.g., uncomplete CVE codes such as CVE-2018, empty contents) and have been removed. Finally, data from the 11 following repositories have been used for extraction: TensorFlow, OpenCV, Ray, NNI, Gym, Scikit-learn, Mxnet, Mlflow, Pytorch, Keras, Deeplearning4j [64].

From the remaining data, CVE IDs are automatically extracted using the regular expression CVE-\d{4}-. Matches the publication year and \d{4,7} matches a unique number of size between 4 and 7. Table 4 shows a sample of comments and titles containing CVE IDs. The gray color highlights search pattern vuln and CVE IDs found. However, the contents of titles and comments can contain threat descriptions without CVE IDs but only external links that point to other links, mailing lists, discussion threads, or other GitHub issues containing CVE IDs (e.g., Red Hat bugzilla, openwall oss-security, Apache mailing lists). Thus, we semi-automatically browsed these descriptions/sub-links/mailing lists/websites to accurately extract those hidden CVE IDs; because doing it only automatically generated a lot of false positives.

Table 5 shows a sample of comments and titles from Pytorch issues that contain hidden CVE IDs. The green color highlights search pattern secur and bold font highlights links/descriptions that allow to retrieve related CVE IDs. The links show that pickle affects torch.load and torch.save calls and mentioned a similar one numpy.load with CVE ID: CVE-2019-6446. In total, 196 CVE IDs have been extracted from the repository issues [64]. We entered CVE codes into the National Vulnerability Database (NVD) and the CVE database to retrieve detailed information such as the severity level of the vulnerability (Step 1), the dependency that caused it, the version (Step 2), and the potential threats that the vulnerability can cause (Step 3). Fig. 5 shows an illustration of this process for the vulnerability CVE-2021-44228 caused by the Log4j dependency (version 2.15, critical score) allowing arbitrary code execution attacks.

Fig. 5: Illustration of an investigation on the NVD database

From the PyPA database, we have also extracted 33 CVE IDs in total from the 9 ML repositories using the previously defined CVE regex (i.e., CVE-\d{4}-.). In the PyPA database, CVE codes are recorded in the YAML format PYSEC-YYYY-UID, where YYYY is the publication year and UID is a unique number. The CVE IDs that were already found in the comments/titles of the 11 remaining repositories from the GitHub search were ignored. In total, we have extracted 226 CVE IDs from the PyPA database and GitHub search. From the extracted data, we semi-automatically build an attack matrix for analysis as follows.

Fig. 6: An illustration of the process for linking tactics to ML phases

3.3.2 Attack correlation matrix
After extraction, attack vectors such as vulnerability and threat are mapped to ML components (models, phases,
The matrix maps threat TTPs to EOIs like

| TTP          | Data Collection | Preprocessing | Feature Engineering | Training | Testing | Inference | Monitoring |
|--------------|-----------------|---------------|---------------------|----------|---------|-----------|------------|
| Reconnaissance | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Resource Development | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Initial Access | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| ML Model Access  | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Execution       | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Persistence     | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Defense Evasion | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Discovery       | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Collection      | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| ML Attack Staging| ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Exfiltration    | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |
| Impact          | ✓               | ✓             | ✓                   | ✓        | ✓       | ✓         | ✓          |

In order to provide findings for RQ1, we have related threat tactics across attacks, similarities in attack execution flows and common entry points. Following the extraction process in Section 3.3.1, we build the threat matrix as shown in Table 6. The cell \('GPT-2 Model Replication', 'Reconnaissance'\) is filled by stage 0; it means the tactic Reconnaissance is used by attack GPT-2 Model Replication. The full table will be described later. Attack CCM is particularly important to analyze the specific effects that an attack vector has on a target component. Attack CCM is divided into two categories: threat CCM and vulnerability CCM. Each category is described below.

**Threat CCM:** The matrix maps threat TTPs to EOIs like attack scenarios and ML phases.

**Mapping between TTP features and attack scenarios.** In order to provide findings for RQ1, we have related threat features (i.e., goals, knowledge, specificity, capability/tactic) of ML threats to attack scenarios for identifying the most used tactics across attacks, similarities in attack execution flows and common entry points. Following the extraction process in Section 3.3.1, we build the threat matrix as shown in Table 6. The coefficients of this matrix can take a string value (e.g., Black-box, stage 0), an empty value when there is no relation between the feature and the attack scenario, or an N/A value meaning that the relation between the feature and the attack scenario is unknown or not mentioned in the database. In the attack capability column, stage i means that the attack scenario executes a given tactic at step i in the attack execution flow. stage i, stage j means that stage i and stage j executes the same tactic.

For example, attack VirusTotal Poisoning starts its execution at stage stage 0 (i.e., Resource Development) in order to purchase tools or infrastructure to support operations. Next, it executes stage stage 1 (i.e., ML Attack Staging) for crafting adversarial data and poison the target model. Then, attacker executes stage stage 2 (i.e., Initial Access) for exploiting valid accounts or external remote services to gain access to unauthorized resources. The attack scenario stops at stage stage 3 (i.e., Persistence) to keep access on the target.

**Mapping between tactics and ML phases.** In order to answer RQ2, tactics are also mapped to ML phases for identifying the frequent threat tactics used against each ML phase. Firstly, we read the ATLAS description of each tactic and their related techniques to find ML phase signatures such as trained, testing the model, use statistics of model prediction scores, and obfuscating/encrypting data. Next, we associate keywords (e.g., inference API) to ML phases (e.g., Inference) following the attack description. An illustration of this process for tactic Defense Evasion is shown in Fig. 6. The tactic URL shows a keyword obfuscating/encrypting data and scripts that clearly affects data manipulation phases such as data collection, pre-processing, and feature engineering. When going further by opening technique Craft Adversarial Data, the technique URL shows that attack can cause misclassification with adversarial examples and get inference API access, which clearly affects testing and inference phases. By going deeper with technique Poison ML Model, it is clearly shown that the attack affects the training phase. Then, the relationship between tactics and ML phases are recorded in a threat CCM for analysis. Table 6 shows a record of the mapping between tactics and ML phases to figure out the impact of threat TTPs against ML phases. The coefficients of this matrix are represented by symbol ✓ when there is a relation between a given tactic and ML phase. Results for RQ2 are provided in Section 4.

**Mapping between attack scenarios and ML models.** To identify ML models targeted/exploited by attack scenarios (as stated in RQ2), the mapping process is done by searching the model type exploited for the attack or a similar attack in the ATLAS TTP descriptions and the attack descriptions from the AI Incident database. When nothing is found, we google the name of the attack scenario and then read related public news and research papers to get the model type of the attack. For instance, the description of the attack scenario Botnet DGA Detection Evasion

The Palo Alto Networks Security AI research team was able to bypass a Convolutional Neural Network (CNN)-based botnet Domain Generation Algorithm (DGA) detection [1] by domain name mutations. indicates that the target model is Convolutional Neural Network \([5]\). Next, the description of the attack scenario Attack on Machine Translation Service

...A research group at UC Berkeley utilized these public endpoints to create an replicated model with near-production...These adversarial inputs ...dropped sentences on Google Translate and Systran Translate websites.
#### TABLE 7: Mapping between TTP features and attack scenarios

| Source                  | Attack scenario                                                                 | Attack Goal        | Attack Knowledge | Attack Specificity | Attack Capability | TTP Features          | TTP Features          | TTP Features          | TTP Features          | TTP Features          | TTP Features          |
|-------------------------|----------------------------------------------------------------------------------|--------------------|------------------|--------------------|-------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| MITRE                   | Evading of Deep Learning Detector for Malware C2 Traffic                        | Integrity          | Black-box         | Advers. Target     | stage 0, stage 1   | stage 2               | stage 3               | stage 1               | stage 0               | stage 2               | stage 1               |
|                        | Unpacking Generation (DGA) Detection Evasion                                   | Integrity          | Black-box         | Advers. Target     | stage 0, stage 1   | stage 3               | stage 2               | stage 0               | stage 2               | stage 1               | stage 0               |
|                        | Virustotal Poisoning                                                            | Integrity          | Black-box         | Advers. Target     | stage 0, stage 2   | stage 1, stage 2     | stage 3               | stage 0               | stage 2               | stage 1               | stage 0               |
|                        | Payment Extortion / AI Malware Detection                                       | Integrity          | Black-box         | Advers. Target     | stage 0, stage 2   | stage 1               | stage 4               | stage 0               | stage 2               | stage 3               | stage 1               |
|                        | Confident Attack on Facial Recognition System                                   | Integrity          | Black-box         | Advers. Target     | stage 0, stage 2   | stage 1               | stage 4               | stage 0               | stage 2               | stage 3               | stage 1               |
|                        | Proof of Concept: Machine Translation Service - Google Translate, Bing Translator, and System Translate | Integrity          | Black-box         | Advers. Target     | stage 0, stage 2   | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | Stealthy Malware Misconfiguration                                              | Integrity          | White-box         | Advers. Target     | stage 0            | stage 0               | stage 2               | stage 2               | stage 3               | stage 5               | stage 7               |
|                        | Proof of Concept: Android Malware Replication                                  | Integrity          | White-box         | Advers. Target     | stage 0, stage 1   | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               | stage 8               |
|                        | Proof of Concept: Evasion                                                      | Integrity          | Black-box         | Advers. Target     | stage 0            | stage 0               | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | Toy Poisoning                                                                  | Integrity          | Black-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | Microsoft Azure Service Disruption                                             | Integrity          | White-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | Microsoft Edge AI Evasion                                                       | Integrity          | Black-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | Track and Interception System Evasion via Physical Countermeasures              | Integrity          | White-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | Backdoor Attack on Deep Learning Models in Mobile Apps                          | Integrity          | White-box         | Advers. Target     | stage 0, stage 2   | stage 0               | stage 1               | stage 4               | stage 2               | stage 3               | stage 5               |
|                        | Smuggled Malware Detection of Neural Networks                                   | Integrity          | Gray-box          | Advers. Target     | stage 0, stage 4   | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
| AI Incident Database    | "Mr. Tug" Shreds an Escalating Political Web                                   | Intentional         | N/A               | Tradition. Target  | stage 0, stage 1   | stage 2               | stage 3               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | Meli Says a Shiraz Denver A Pro-Russian Disinformation Network                  | Intentional         | N/A               | Tradition. Target  | stage 0, stage 1   | stage 2               | stage 3               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | Yahoo loggers Attacked by a Potentially Unaided Drone, UN Says                  | Intentional         | N/A               | Tradition. Target  | stage 0            | stage 0               | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | Translators’ Ousted Company Director’s Voice In SWIM Bank, Heat, Polska Fund   | Integrity          | N/A               | Tradition. Target  | stage 0            | stage 0               | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | KZN Park’s High-Tech Security and Kill Four Rhinos for their Homes            | Intentional         | N/A               | Tradition. Target  | stage 0            | stage 0               | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | Lebanese Rami Security Lab Experimental Security Research of Tesla Autopilot   | Integrity          | White-box         | Advers. Target     | stage 0            | stage 0               | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | Three-Wave Attack in Intersection Can Cause Tesla Autopilot to Reserve Info Wrong Lane | Integrity          | White-box         | Advers. Target     | stage 0            | stage 0               | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | He's MAN Black - Steal SMM The Hard Fork                                       | N/A                | Tradition. Target | stage 0            | stage 0               | stage 1               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
| Literature              | Carlini et al. [44]                                                            | Intentional         | Black-box         | Advers. Target     | stage 0, stage 1   | stage 2               | stage 3               | stage 2               | stage 3               | stage 4               | stage 5               |
|                        | 2018 by the Benjaminet al.                                                     | Intentional         | Gray-box          | Advers. Target & Target & Unarget | stage 1 | stage 0 | stage 2 | stage 1 | stage 0 | stage 2 | stage 3 | stage 4 | stage 5 | stage 6 |
|                        | 2017 by the Benaroni et al.                                                     | Intentional         | Gray-box          | Advers. Target & Target & Unarget | stage 1 | stage 0 | stage 2 | stage 1 | stage 0 | stage 2 | stage 3 | stage 4 | stage 5 | stage 6 |
|                        | 2016 by the Carlini et al.                                                      | Intentional         | Black-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | 2015 by the Abrallah et al.                                                     | Intentional         | White-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | 2014 by the Chen et al.                                                         | Intentional         | White-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | 2018 by the Choquette-Che et al. [37]                                            | Intentional         | Black-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | 2018 by the Papernot et al.                                                     | Intentional         | Black-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | 2018 by the Goodhew et al.                                                      | Intentional         | White-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | 2018 by the Papernot et al.                                                     | Intentional         | Black-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | 2018 by the Carlini et al.                                                      | Intentional         | Gray-box          | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |
|                        | 2018 by the Athalye et al.                                                      | Intentional         | White-box         | Advers. Target & Target & Unarget | stage 1 | stage 0 | stage 2 | stage 1 | stage 0 | stage 2 | stage 3 | stage 4 | stage 5 | stage 6 |
|                        | 2017 by the Jagielski et al.                                                    | Intentional         | White-box         | Advers. Target     | stage 0, stage 1   | stage 0               | stage 2               | stage 3               | stage 4               | stage 5               | stage 6               |

**Notes:**
- **Intentional** refers to intentional attacks.
- **Target** and **Unarget** indicate whether the attack is specifically targeted or not.
TABLE 8: Mapping between attack scenarios and ML models

| Source | Attack scenario | Model Used |
|--------|----------------|------------|
| MITRE | Evasion of Deep Learning Detector for Malware C2 Traffic | CNN |
|       | Botnet Domain Generation (DGA) Detection Evasion | CNN |
|       | Virus Total Poisoning | LSTM |
|       | Bypassing Cyantine’s AI Malware Detection | DNN |
|       | Camera Hijack Attack on Facial Recognition System | CNN, GAN |
|       | Attack on Machine Translation Service - Google Translate, Bing Translator, and Synchron Translate | Transformer |
| ATLAS | Clearview AI Misconfiguration | N/A |
|       | GPT-2 Model Replication | GPT-2 |
|       | Proof of Point Evasion | Copycat [67] |
|       | IIS Poisoning | DNN |
|       | Microsoft Azure Service Disruption | N/A |
|       | Microsoft Edge AI Evasion | DNN |
|       | Face Identification System Evasion via Physical Counter measures | N/A |
|       | Backdoor Attack on Deep Learning Models in Mobile Apps | DNN |
|       | Confusing AntiMalware Neural Networks | DNN |
|       | India’s Ick Fog Shrouts an Escalating Political War | GPT-2 |
|       | Meta Says It’s Shut Down A Pro-Russian DisInformation Network... | N/A |
|       | Libyan fighters Attacked by a Potentially Unnaied Drone, UN Says | CNN |
|       | Fraudsters Cloned Company Director’s Voice In $35M Bank Heist, Police Find | DeepVoice [68] |
|       | Poachers Evade KZN Park’s High-Tech Security and Kill four Rhinos for their Horns | DNN |
|       | Tencent Keen Security Lab: Experimental Security Research of Tesla Autopilot | Fisheye [69] |
|       | Three Small Stickers in Intersection Can Cause Tesla Autopilot to Sverve Into Wrong Lane | CNN |
|       | The DAO Hack Stolen $33M The Hard Fork | N/A |
|       | Carlini et al. [4] | GPT-2 |
|       | Biggio et al. [32] | SVM, DNN |
|       | Barreno et al. [35] | Naive Bayes |
|       | Carlini et al. [36] | Feed-Forward DNN |
|       | Wallace et al. [67] | Transformer |
|       | Abdulllah et al. [53] | RNN, CNN, Hidden Markov |
|       | Chen et al. [51] | LSTM, BERT |
|       | Choquette-Choo et al. [57] | CNN, RestNet |
|       | Papernot et al. [50] | LN, CNN, SVM, Logistic Regression Decision Trees |
|       | Goodfellow et al. [59] | GAN |
|       | Papernot et al. [60] | DNN |
|       | Cisse et al. [61] | Parseval Networks |
|       | Athalye et al. [62] | CNN, ResNet, InceptionV3 |
|       | Jagielski et al. [17] | RestNetv2 |

do not contain information about the replication model used [65]. Thus, we google the attack scenario title and it pointed to the paper [57]. This paper allowed us to figure out that the replication was based on the Transformer model and Knowledge Distillation [57]. Then, the targeted/exploited ML models and attack scenarios are recorded in a threat CCM for analysis.

Table 9 shows the mapping between attack scenarios and ML models per dataset to figure out the impact of threat TTPs against ML models. Attack scenarios exploited/targeted 16 specific model architectures such as Convolutional Neural Network (CNN), Long Short Term Memories (LSTM), Generative Adversarial Network (GAN), Generative Pretrained Transformer (GPT), DeepVoice [68], Support Vector Machine (SVM), Recurrent Neural Network (RNN), Feed-Forward Neural Network (FFNN), Copycat CNN [67], Residual Neural Network (ResNet), Fisheye CNN [69], Logistic Regression, k-Nearest Neighbor (kNN), Decision Tree (DT), Parseval Network, InceptionV3, Hidden Markov Model (HMM), Naive Bayes, and Bidirectional Encoder Representations from Transformer (BERT). Other ML attacks exploited/targeted Deep Neural Networks (DNNs) or Transformers but the type is unknown. Some model architectures used by threat actors were unknown after several researches and the notation N/A is used in such case. Results for RQ2 are provided in Section 4.

Vulnerability CCM: The matrix maps vulnerabilities to EOs like ML repositories. To get findings for RQ3, CVE IDs found in repository issues and those from the PyPA database have been mapped to ML repositories for identifying the most prominent vulnerabilities and threats in ML repositories as well as the dependencies that cause them (see Fig. 5). The mapping relation between an CVE ID and a given ML tool is represented by a tuple (dep, att, lvl), where dep is the name of the dependency that caused the attack; att = this if it is the main tool, att is the name of the attack that can be launched to exploit a CVE vulnerability, and lvl is the severity level of the vulnerability.

In Table 9, an illustration of the mapping is described using vulnerability extraction process in Table 3 and Table 5. The cell (CVE-2022-29216, tensorflow) has value (this, code injection, high). It means that Tensorflow framework is vulnerable to code injection with a high severity. In addition, the cell (CVE-2019-6446, nni) has value (pickle, arbitrary-code-exec, critical), meaning that the dependency pickle has the highest severity level (i.e., critical) and it can allow arbitrary code execution (arbitrary-code-exec) attacks in the Microsoft Neural Network Intelligence (NNI) tool. The full tables can be found in [64].

3.3.3 Metrics
We compute the following metrics to answer our research questions.

RQ1. For this question, the metric used is the number of attacks that used a given tactic and the tactic. It provides information about the most exploited tactics by attack scenarios.

RQ2. The metric used is the number of tactics that target a given phase and the phase targeted. It gives information about ML phases that are more impacted/targeted by ML
RQ3. For this question, the metrics are the number of vulnerabilities (nov) and the vulnerability type, the nov per tool, and the nov per type per tool. They provide information about the prominence of vulnerabilities in the ML repositories, the most affected repositories, and the potential threats.

4 Study results

In this section, we present and discuss the results of our research questions.

4.1 Prominence and common entry points of threat TTPs exploited in ML attack scenarios (RQ1)

This research question is divided into two parts: the prominence of threat TTPs exploited in attack scenarios and the common entry points.

The prominence of threat TTPs in attack scenarios

Table 7 shows the mapping between tactics and attack scenarios. The most prominent tactic is ML Attack Staging; since it occurs 30 times across the 89 ML attack scenarios. During ML attack staging, threat actors prepare their attack by crafting adversarial data to feed the target model, training proxy models, poisoning or evading the target model. The other significant tactics used in attack scenarios are Impact and Resource Development; since they respectively occur 21 times and 15 times in ML attack scenarios (see Table 7). After the ML attack success, most attack scenarios tried to evade ML model, disrupt ML service, or destroy ML systems, data, and humans (Impact).

In Table 7 the execution flows of attack scenarios share some TTP stages. The most used TTP sequences in attack scenarios are:

- **ML Attack Staging (stage 0) → Impact (stage 1)**
- **Reconnaissance (stage 0) → Resource Development (stage 1) → ML Model Access (stage 2) → ML Attack Staging (stage 3) → Impact (stage 4)**
- **Reconnaissance (stage 0) → Resource Development (stage 1) → ML Attack Staging (stage 2) → Defense Evasion (stage 3)**

since attack scenarios (Carlini et al. [56], Abdullah et al. [33], Papernot et al. [58], Biggio et al. [34], Athalye et al. [62], Barreno et al. [55]) have similar execution sequences i.e., starting from stage 0 to stage 2. Attack scenarios (Carlini et al. [4], Wallace et al. [57], Choquette-Choo et al. [37]) share stages from stage 0 to stage 1. In addition, attack scenarios Attack on Machine Translation Service and Microsoft Edge AI Evasion have similar execution sequences i.e., starting from stage 50 to stage 54. It is also the same for attack scenarios Evasion of Deep Learning Detector for Malware C2 Traffic and Botnet Domain Generation (DGA) Detection Evasion that share stages from stage 0 to stage 3. Attack scenarios Jagielski et al. [17] and Poachers Evade KZN’s Park High-Tech Security have some stages already included in the selected sequences, i.e., Defense Evasion (stage 0) and Impact (stage 1), ML Attack Staging (stage 1) and Exfiltration (stage 2). Attack scenarios Backdoor Attack on Deep Learning Models in Mobile Apps and Confusing AntiMalware Neural Networks only share two stages (i.e., stage 0 and stage 1) already included in the selected sequences; thus, they are ignored.

Table 7 also shows that the most attack scenarios targeted ML systems without a prior knowledge or access of the training data and the ML model (black box); this is explained by the highest number of occurrences of Blackbox in the Attack Knowledge column (i.e., 17 times). In addition, most attack scenarios are untargeted, shown by the highest number of occurrences of Traditional Untargeted and Adversarially Untargeted in the Attack Specificity column (i.e., 20 times). They also mainly targeted Confidentiality and Integrity.
4.2 Impact of threat TTPs against ML phases and models (RQ2)

This research question aims to identify the most targeted/vulnerable ML phases and models and the most used threat TTPs across different ML phases. Therefore, the question is divided into two parts: the impact of threat TTPs against ML phases and the impact of threat TTPs against ML models.

Impact of threat TTPs against ML phases

In Table 6, the most targeted phases are Testing, Inference, Training, and Data collection. Tactics Reconnaissance, Impact, ML Attack Staging, and Resource Development are the most used across the different ML phases.

 TABLE 10: Statistics about models used in attack scenarios

| Models used | Occurrences per attack | Attack Period |
|-------------|------------------------|---------------|
| Transformers (BERT, GTP-2, GPT-3, others) | 6 | 2019-2022 |
| Convolutional Neural Networks (CopyCat, Fisheye, ResNet, others) | 11 | 2018-2021 |
| Deep Neural Networks (unspecified) | 9 | 2013-2021 |
| Hidden Markov | 1 | 2021 |
| Long-Short Term Memory | 2 | 2020-2021 |
| Generative Adversarial Networks | 2 | 2014-2020 |
| DeepVoice [68] | 1 | 2019 |
| Feed-Forward Neural Networks | 1 | 2017 |
| Parseval Networks | 1 | 2017 |
| Linear classifiers (SVM, Logistic Reg., Naive Bayes) | 3 | 2010-2016 |
| Non-Linear classifiers (Decision Trees, k-Nearest Neighbor) | 2 | 2016 |
| N/A | 5 | 2018-2022 |

4.3 Finding new threats in the AI Incident database, the literature, and ML repositories that are not documented in ATLAS (RQ3)

To achieve this goal, the question is split into three parts: the new threats from the AI Incident database and the literature, and the potential threats from the ML repositories, the most vulnerable ML repositories as well as the dependencies that cause them, and the most frequent vulnerabilities in the ML repositories.

The new threats from the AI Incident Database and the literature

In Table 2, we have identified new TTPs (i.e., 9 techniques, 7 tactics) from the 8 ML attacks in the AI Incident database. The attack techniques used are Establish Accounts, Valid Accounts, Create Proxy ML model: Use Pre-Trained Model, Exfiltration via Cyber Means, Active Scanning, Cost Harvesting,
Evade ML Model, Craft Adversarial Data, and ML Denial of Service. The attack tactics used are Resource Development, Initial Access, ML Attack Staging, Exfiltration, Reconnaisance, Impact, and Defense Evasion.

Table 3 also shows TTPs extracted from the 14 ML attacks in literature (i.e., 8 techniques, 6 tactics) following ATLAS TTP definitions. The attack techniques used are Create Proxy ML model; Use Pre-Trained Model, Exfiltration via ML Inference API; Extract ML Model, Craft Adversarial Data, Evade ML Model, Craft Adversarial Data: Insert Backdoor Trigger, Backdoor ML Model: Inject Payload, Exfiltration via ML Inference API; Infer Training Data Membership, and Search for Victim’s Publicly Available Research Materials. The attack tactics used are ML Attack Staging, Exfiltration, Defense Evasion, Impact, Persistence, and Reconnaissance.

These 32 new ML attack scenarios were not documented in ATLAS and can be used to complete ATLAS case studies.

The potential threats from vulnerabilities in the ML repositories

Most threats found in ML repositories were of two categories: software-level and network-level. Fig. 7 shows 16 vulnerability types found in the studied ML repositories from the GitHub search and their occurrences. These 16 vulnerabilities can be exploited to cause more than 16 threats on ML systems; since a single vulnerability can cause several damages. Potential threats are grouped as follows: (1) software-level threats include arbitrary code execution, buffer overflow, denial-of-service (DoS), out-of-bounds (read/write), use-after-free (UAF), code injection, null-pointer dereference, untrusted-deserialization, improper validation, excessive iteration, divide-by-zero, reachable assertion, crash-insufficient information; and (2) network-level threats include remote code execution (RCE), cross-site scripting (XSS), and credentials discovery sniffing. In addition, we want to highlight that software-level DoS are different from network-level DoS that disrupts the normal traffic of a network resource. Software-level DoS can be a memory or crash error (e.g., segmentation fault) that causes disruption of the underlying OS and machine. Threats such as out-of-bounds, buffer overflow, improper validation, code injection, DoS, and excessive iteration were the most prominent in ML repositories extracted from GitHub.

Fig. 8 shows 14 additional vulnerability types found in the PyPA database and their occurrences. The 14 potential threats are grouped as follows: (1) software-level threats include DoS, buffer overflow, null-pointer dereference, arbitrary code execution, user impersonation, command execution, cleartext storage, inefficient regex complexity, symlink; and (2) network-level threats include XSS, cross site request forgery (CSRF), cross site inclusion, directory transversal, and open redirect. The most prominent threats in ML repositories from the PyPA database are XSS, arbitrary code execution, open redirect, DoS, and buffer-overflow.

Globally, buffer-overflow and DoS are prominent in both ML repositories obtained from GitHub and the PyPA database.

The most vulnerable ML repositories as well as the dependencies that cause them

Fig. 9 shows the vulnerability importance per tool (from the GitHub search)

- The most prominent threats in ML repositories extracted from GitHub are out-of-bounds, buffer overflow, improper validation, code injection, and DoS
- The most prominent threats in ML repositories from the PyPA database are XSS, arbitrary code execution, open redirect, DoS, and buffer-overflow
- The most prominent threats in both ML repositories are buffer-overflow and DoS
- 32 new ML attack scenarios (i.e., 17 techniques, 13 tactics) have been identified and can be used to complete ATLAS case studies for future research.
TABLE 11: Dependencies that caused vulnerabilities in repositories

| dependency         | vuln. num. caused | affected repos. | severity (avg.) |
|--------------------|-------------------|-----------------|-----------------|
| yaml               | 1                 | tensorflow      | high            |
| sqlite3            | 16                | tensorflow      | high            |
| libjpeg-turbo      | 4                 | tensorflow      | medium          |
| giflib             | 1                 | tensorflow      | medium          |
| icu                | 1                 | tensorflow      | high            |
| libjpeg-9c         | 1                 | tensorflow      | high            |
| libpng             | 1                 | opencv          | high            |
| lua54              | 5                 | ray             | high            |
| pickle             | 4                 | nni, pytorch, pandas, numpy | critical |
| requests           | 1                 | mxnet           | high            |
| pyyaml             | 1                 | nni             | high            |
| pillow             | 1                 | gym             | high            |
| log4j              | 3                 | ray, mllow      | high            |
| numpy116           | 1                 | nni             | critical        |
| joblib             | 1                 | scikit-learn    | critical        |
| libsvm             | 1                 | scikit-learn    | high            |
| python391          | 1                 | pytorch         | critical        |
| jupyter21          | 1                 | keras           | medium          |
| curl/libcurl/      | 17                | tensorflow      | high            |
| commons-compress118| 1                 | deeplearning4j | high            |
| jackson-bind100    | 1                 | deeplearning4j | high            |
| snakeyaml124       | 1                 | deeplearning4j | high            |
| psutil             | 1                 | tensorflow      | high            |

The most vulnerable ML repositories from the GitHub search are TensorFlow, OpenCV, Ray, and NNI. The most vulnerable ML repositories from the PyPA database are Scikit-Learn, Pytorch, Keras, Mlflow, and Mxnet. The most severe dependencies causing the vulnerabilities are pickle, joblib, numpy116, python391, log4j, sqlitedb, pillow, curl/libcurl7, snakeyaml124, commons-compress118, jackson-bind100, lua54, pyyaml, libjpeg-9c, libsvm, icu, requests, and psutil.

Summary 4

- The most vulnerable ML repositories from the GitHub search are TensorFlow, OpenCV, Ray, and NNI.
- The most vulnerable ML repositories from the PyPA database are Scikit-Learn, Pytorch, Keras, Mlflow, and Mxnet.
- The most severe dependencies causing the vulnerabilities are pickle, joblib, numpy116, python391, log4j, sqlitedb, pillow, curl/libcurl7, snakeyaml124, commons-compress118, jackson-bind100, lua54, pyyaml, libjpeg-9c, libsvm, icu, requests, and psutil.

Dependencies like pickle, numpy116 (version 1.16.0), joblib, and python391 (version 3.9.1 of python) have a critical severity and affected the following repositories: Pytorch, NNI, Pandas, Numpy, and Scikit-Learn. Deeplearning4j was affected by 3 dependencies with high severity: commons-compress118 (Apache version 1.18), jackson-bind100 (version...
1.0.0 beta7), and *snakeyaml*1.24 (version 1.24). ML repositories such as Ray and MLflow were affected by the Log4j dependency which has a high severity. Other repositories such as OpenCV and Mxnet are respectively affected by libpng and requests dependencies with high severity.

After identifying vulnerabilities and the dependencies that caused them, we want to know how they propagated across the studied ML repositories. Fig. 10 shows the vulnerability distribution in ML repositories obtained from the GitHub search. The most frequent vulnerability is DoS. It occurs in 6 repositories: TensorFlow, OpenCV, Deeplearning4j, Ray, Scikit-Learn, and Gym. The next ones are arbitrary code execution, RCE, UAF, and buffer overflow. The arbitrary code execution vulnerability is found in 3 repositories: TensorFlow, NNI, and Pytorch. RCE spreads on 3 repositories: OpenCV, Ray, and MLflow. UAF occurs in 3 repositories: TensorFlow, OpenCV, and Ray. Buffer overflow is found in 3 repositories: TensorFlow, OpenCV, and Pytorch. Other vulnerabilities such as out-of-bounds, code-injection, null-pointer dereference, and credential snifffing were respectively detected in 2 repositories (i.e., OpenCV and Ray, TensorFlow and OpenCV, TensorFlow and Deeplearning4j, TensorFlow and Mxnet).

Fig. 11 shows the vulnerability distribution in ML repositories from the PyPA database. The most frequent vulnerability is arbitrary code execution. It occurs in 3 repositories: Notebook, Pandas, and Numpy. Then, other vulnerabilities such as XSS, DoS, buffer overflow, and open redirect are found in 2 repositories; respectively, Notebook and Jupyterlab, Numpy and NLTK, Numpy and Protobuf, Notebook and Jupyter-server.

5 Mitigation of Vulnerabilities and Threats

The previous sections identified and characterized ML threats, as well as their impact on ML components (models, phases, tools). In order to answer to RQ4, we provide proactive and reactive countermeasures that could be used to mitigate these ML threats. Based on security guidance from MITRE ATT&CK [44], MITRE D3FEND [24], NIST security guidelines [46]–[52], and the Cloud Security Alliance [45], we propose a mitigation matrix to help harden ML assets, detect vulnerability and threats on ML assets, isolate and evict infected ML assets from data level to cloud level during the ML lifecycle (see Fig. 13). In the following, some mitigations are described and the documentation in progress can be found in [64].

At data level, hardening techniques include adversarial defenses [8], [11], [73], and tools such as ART, cleverhans, foolbox. Code signing certificates [52] can be used to ensure authenticity and integrity of the data sources. Data protection [45], [50] can be enforced in transit by using TLS.
encryption to secure ML API calls, at rest by using AES-based keys for protecting ML assets during ML phases, and in use by dynamic analysis of data. Proper identity and access management (IAM) based on the least privilege [46, 74, 75] can be used to limit unintended access on ML artifacts such as training data, ML models, model parameters, and model results produced/used during ML phases. To detect adversarial examples, techniques such as Introspection [26], Feature Squeezing [76], and SafetyNet [77] can be used. When an attack is identified, infected training data and ML models can be stored in isolated databases/cloud environments [78]. Then, training data and ML models can be deleted or sanitized using denoisers [79–81].

At software level, regular vulnerability scanning of ML libraries, ML pipeline and model source code [49] can be used to mitigate vulnerabilities in ML systems using tools such as GitHub code scanning, Tsunami, OSS-fuzz, and SonaQube. IAM based on least privilege [46] can be enforced on running processes, applications, containers, and virtual machines to restrict accesses on premises and off premises. At database level, proper IAM configuration [46, 74, 75] can be used to limit database accesses. Database backup must be regularly done and kept separate from the corporate network to prevent compromise [82]. At system level, proper OS hardening [48] such as automatic system updates, Secure Boot enabling and configuration, and limitation of access permission can be enforced to secure the ML system endpoints. Regular patch management [48] with up-to-date ML libraries can be enforced to mitigate the vulnerabilities in ML systems. For threat detection, ML infrastructures can use endpoint detection and response (EDRs) or antivirus (e.g., Microsoft Defender, Wazuh), security information and event management systems (SIEMs), audit and logging.

At network level, network access control lists [47, 83, 84] can be applied to virtual private clouds (VPCs) to control traffic access for virtual machine instances of the ML infrastructure. Firewalls [85] and Intrusion Prevention Systems (IPS) [86] can be installed as first line of defense to analyze and take immediate actions when a malicious traffic is observed. Encrypted tunnels (e.g., IPSec VPN [84]) can be used to ensure end-to-end security of remote accesses in the corporate network and external networks (e.g., partners, customers). At cloud level, security mechanisms [45, 87] include IAM with policies based on least privilege, role-based permissions, and multi-factor authentication (MFA); enforcing cloud security policies using solutions such as cloud access security broker (CASB), Zero trust [25, 88], and access service edge (SAE); endpoint protection using EDRs (e.g., Falcon Insight, Cortex XDR, Microsoft Defender); network prevention and detection systems (e.g., Snort, Zeek); cloud-based SIEMs (e.g., Splunk Cloud, Azure Sentinel); setting of bastion/transit virtual networks for more-flexible hybrid clouds; auditing and logging.

6 Threats to validity

ATLAS is a new database less mature than ATT&CK (e.g., it does not yet have specific mitigation definitions for ML threats, there is no tool support). In addition, The AI Incident database is used to collect new threat feeds but does not provide clear information of the TTPs and models used for the attacks; thus limiting the scope of the study. Moreover, mining vulnerabilities in large ML repositories is a challenging task that requires automation and can be slow. Some vulnerabilities cannot be found because some maintainers did not report them through issues or security advisories. Moreover, searching for hidden vulnerabilities from references in issues (i.e., mailing lists, discussion threads, websites) is time-consuming and some vulnerabilities could be missed. Precisely, issue comments and references often contain CVE codes with typo errors (e.g., CVE-2018 without the number) or non-ascii parts (e.g., CVE-2017\x0124) that could be missed using regular expressions. Nevertheless, we spent effort to systematically collect threat/vulnerability data while ensuring they are reliable. We also proposed mitigations for each specific ML phase and asset to ensure threat prevention.

7 Conclusion

In this work, we have studied ML threat behaviors and analyzed the impact of these threats on ML components using ATLAS and AI Incident databases; and ML repositories from GitHub and the PyPA database. Results show that CNNs were one of the most targeted in attack scenarios. Our examinations of vulnerabilities and attacks reveal that testing, inference, training are the most targeted ML phases by threat actors. Threats like buffer-overflow and DoS were the most frequent threats in the studied ML repositories. ML repositories such as TensorFlow, OpenCV, and Notebook have the largest vulnerability prominence and the most severe dependencies causing them include pickle, joblib, numpy116, python3.9.1, and log4j. 32 new ML attack scenarios (17 techniques, 13 tactics) have been identified and can be used to complete ATLAS case studies for future research. To help mitigate these threats, we have proposed an ML threat mitigation matrix to help defend against real-world threats targeting ML products and ML cloud infrastructures. In the future, we plan to implement a ML threat assessment tool to continuously ingest various vulnerability feeds, TTP definitions from several ML threat databases; and generate attack matrices and analytic graphs in real-time using Natural Language Processing techniques. We also plan to contribute to the development of tools to support the ATLAS framework.

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