Adversarial Machine Learning Threat Analysis in Open Radio Access Networks

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Abstract—The Open Radio Access Network (O-RAN) is a new, open, adaptive, and intelligent RAN architecture. Motivated by the success of artificial intelligence in other domains, O-RAN strives to leverage machine learning (ML) to automatically and efficiently manage network resources in diverse use cases such as traffic steering, quality of experience prediction, and anomaly detection. Unfortunately, ML-based systems are not free of vulnerabilities; specifically, they suffer from a special type of logical vulnerabilities that stem from the inherent limitations of the learning algorithms. To exploit these vulnerabilities, an adversary can utilize an attack technique referred to as adversarial machine learning (AML). These special type of attacks has already been demonstrated in recent researches. In this paper, we present a systematic AML threat analysis for the O-RAN. We start by reviewing relevant ML use cases and analyzing the different ML workflow deployment scenarios in O-RAN. Then, we define the threat model, identifying potential adversaries, enumerating their adversarial capabilities, and analyzing their main goals. Finally, we explore the various AML threats in the O-RAN and review a large number of attacks that can be performed to materialize these threats and demonstrate an AML attack on a traffic steering model.

Index Terms—Open radio access networks, adversarial machine learning, security and privacy, threat analysis

I. INTRODUCTION

In recent years, the number of cellular network users has increased dramatically. According to Statista's 2021 report, in 2021 there were 15 billion unique mobile devices, a number which is expected to reach 18.22 billion by 2025. There has also been rapid growth in the number of connected IoT devices, with a projection of 27 billion connected IoT devices in 2025, and thus, the requirements of the cellular network are not limited to just mobile devices. Currently, cellular networks must support a diverse set of use cases, including smartphones and smart watches, drones, industrial IoT devices, distributed sensors, and connected cars. New devices, use cases and applications pose new challenges for cellular networks. Such challenges include the need to serve billions of devices, while maintaining low expenses, and the need to offer adaptive bandwidth and latency requirements, in real time, for different applications and use cases.

A. The Open Radio Access Network

In order to support new cellular network requirements, vendors have started investigating new radio access network (RAN) architectures. A promising RAN architecture that has gained worldwide acceptance is the Open Radio Access Network (O-RAN), which was suggested by the O-RAN Alliance [1]. The O-RAN Alliance (founded in February 2018 by AT&T, China Mobile, Deutsche Telekom, NTT DOCOMO, and Orange) is a worldwide community of mobile network operators, vendors, and academic institutes. The alliance's vision is to reshape the RAN industry toward the establishment of an open, adaptive, and intelligent RAN.

O-RAN’s Vision: key objectives defined by the alliance

| Open | All design documents, interfaces, and software must be open. The openness aspect promotes multi-vendor deployments with open interfaces between all decoupled RAN components, enabling a more competitive ecosystem. |
| Adaptive | RAN components must be able to adapt themselves, in real time, to support different use cases and service requirements. To achieve this goal, the alliance promotes the cloudification of the RAN technology and an overall shift to cloud-native technologies, where network components are virtualized and controlled by software-defined networking. Cloudification facilitates flexible resource provisioning and enables centralization of the RAN infrastructure and a reduction of operational costs. |
| Intelligent | RAN management must not rely on human intensive means. Motivated by the success of artificial intelligence and machine learning (ML) in other domains, the O-RAN strives to leverage ML for efficient automated network resource management. This includes a large set of use cases such as: traffic steering, quality of experience prediction, network traffic prediction, and anomaly detection. |

B. Security of the O-RAN

The introduction of new concepts and technologies into the RAN is promising in terms of meeting the new requirements. Unfortunately, when new technologies are introduced, they are accompanied by new cybersecurity threats; as a result, the RAN’s attack surface may change dramatically when integrating new technologies. Understanding the new attack surface is crucial for securing the new Open RAN architecture.

Recent studies have provided a throughout security analysis of the new Open RAN architecture, however
these papers mainly focused on (a) reviewing recent attacks on the traditional RAN and evaluating their applicability to the O-RAN; (b) reviewing recent attacks on cloud environments and evaluating their applicability to the O-RAN; and (c) reviewing threats to open-source architectures and evaluating their impact on the O-RAN. To the best of our knowledge, no recent studies have evaluated the security threats introduced by the use of ML in the O-RAN; i.e., the robustness of the O-RAN to adversarial machine learning threats.

C. Adversarial Machine Learning

ML systems are not vulnerability-free. Specifically, ML systems suffer from a special type of logical vulnerabilities that stem from inherent limitations of the underlying learning algorithm. To exploit these vulnerabilities, attackers utilize an attack technique referred to as adversarial machine learning (AML), which has already been demonstrated in security and ML research [6], [39], [17]. For example, in the evasion threat [6], [15], [22], the adversary may exploit the ML model by generating an input sample that is very similar to some other correctly classified input but is incorrectly classified by the model [6]. In this case, the adversary’s main objective is to compromise the integrity of the ML model by causing the model to provide incorrect outputs for a specific input generated by the attacker. The evasion threat is just one example of AML. Other studies have demonstrated additional threats to ML models, including (a) privacy threats (such as membership inference [36], [30]), data property inference [3], [14], [38], data reconstruction [13], [16], and model extraction [7], [20], [31], [32]; and (b) availability threats (such as model corruption [21], [27], [18]) and resource exhaustion [37].

D. Scope and Purpose

In this research, we present a systematic AML threat analysis of the O-RAN. We begin by describing the O-RAN architecture (Section II). Then, we review the various ML use cases applicable to the O-RAN and analyze the different deployment scenarios of ML workflows in the O-RAN (Section III). In Section V, we describe the proposed threat model, which outlines the capabilities needed by an attacker to perform AML attacks. In that section, we also identify potential threat actors in the O-RAN ecosystem and map them to the abovementioned capabilities. In Section VI, we evaluate the various AML threats applicable to the O-RAN; for each threat, also we review various attack techniques. Finally, in Section VII, we demonstrate the applicability of an AML attack on the traffic steering use case implemented in the O-RAN reference implementation.

II. THE O-RAN ARCHITECTURE

The RAN provides wireless connectivity to mobile devices and acts as the final link between the cellular network and user equipment. A typical RAN is composed of a radio unit (RU) and a base station (containing baseband units/BBUs). In older mobile network generations (prior to 4G), the electronic equipment of the RU and BBU were coupled together at the bottom of the mobile antenna towers, and RF cables were used to connect the RU to the antennas at the top of the towers. However, this approach was inefficient in terms of the signal performance, and eventually, the cellular industry relocated the RU equipment to the top of the tower.

A traditional RAN is vendor proprietary. That is, the interfaces between the RU and the BBU are defined by the vendor, and the applications running on them are tailored and optimized to the specific vendor’s equipment. Vendor-specific solutions allowed vendors to provide optimized, integrated solutions; however, it may be sub-optimal. In addition, a proprietary RAN requires the vendor to develop all of the components, which increases the cost of the RAN for operators and increases the operators’ dependence on the vendor.

During the 4G and 5G, the RAN architecture has evolved, becoming less centralized and more disaggregated while transitioning from the use of dedicated equipment and software to the use of general-purpose hardware, virtualization, and the adoption of cloud-native technologies. While decentralization mainly reduces costs, disaggregation allows deployment flexibility and accommodates the diversity of 5G use cases.

In Figure 1, we present the disaggregated and open architecture introduced by the O-RAN alliance. A brief description of the various components and protocols introduced in O-RAN is presented in Table I.

III. MACHINE LEARNING IN THE O-RAN

Artificial intelligence (AI) and machine learning (ML) play a crucial role in the 5G network in general and in the vision of O-RAN in particular. For example, in 5G networks, ML is used for network planning, automation of network operations (such as provisioning, optimization, and fault prediction), network slicing, and quality of service prediction. In this section, we review
the deployment of ML workflows in the O-RAN. In Table II, we review the various components of a typical ML workflow (also illustrated in Figure 2).

A. The Deployment of ML workflows in the O-RAN

As presented in Figure 3, there are five different ML-based application deployment scenarios in the O-RAN which are defined by the type of ML task and the application’s latency requirements. Specifically, the O-RAN architecture supports three main types of ML tasks: supervised learning, unsupervised learning, and reinforcement learning, and three levels of latency requirements: high latency, low latency, and ultra-low latency. According to the current design document of the O-RAN, the various ML components can be implemented on the following four O-RAN units: (1) the Non-RT RIC, (2) the Near-RT RIC, (3) the O-CU (inference only), and (4) the O-DU (inference only); currently, ML components cannot be implemented on O-RUs.

In Figure 3, we present the deployment of the different ML components (data collection, data host, training host, serving host, and ML APP host) within the different layers of the O-RAN (O-CU/O-DU, Near-RT RIC, and Non-RT RIC) for each deployment scenario according to the ML task and required latency.

### Table I: The various components and interfaces in O-RAN.

| Component | Description |
|-----------|-------------|
| User equipment (UE) | The UE is the end user’s device (e.g., smartphone, connected car, smart IoT sensor), which consumes network services from the cellular network over a radio channel. |
| O-RAN radio unit (O-RU) | The RU is responsible for the broadcast and transmission of radio frequency signals, and it is usually part of the antenna. It provides the physical layer functionality. |
| O-RAN distributed unit (O-DU) | The DU is responsible for real-time scheduling functions. |
| O-RAN centralized unit (O-CU) | The CU is composed of two modules: central unit-control plane (CU-CP) and central unit-user plane (CU-UP). The CU-CP is a logical node hosting the radio resource control and the control plane part of the packet data convergence protocol (PDCP). The CU-UP is a logical node hosting the service data adaptation protocol and the user plane (UP) part of PDCP protocol. The rationale behind this separation is to improve the placement of different RAN functions, thereby accommodating different situations and performance needs. |
| Near-RT RIC | An intelligent controller that enables near real-time control and optimization of RAN elements and resources. It is implemented as a (private/public) cloud platform, which support low latency. |
| Service management & orchestration (SMO) | This component holds management services for fault, configuration, accounting, performance, and security (FCAPS). |
| Non-RT RIC | This module supports intelligent RAN optimization. It provides policy-based guidance, ML pipeline management (e.g., hosting, training, updating), and enrichment information for the Near-RT RIC. |
| O-RAN Interfaces | The interface between the O-DU and the O-RU; it includes the control user synchronization plane and management plane (M-Plane). |
| Open Fronthaul M-Plane | The interface between the SMO and the management entity (e.g., O-DU, O-RU, O-CU). This interface supports FCAPS management, physical network function (PNF) software management, and file management. |
| O1 | The interface between the O-DU and the O-RU; it includes the control user synchronization plane and management plane (M-Plane). |
| O2 | The interface between the SMO and the O-CU. This interface supports infrastructure management services and deployment management services. |

### Table II: The various components of a typical ML workflow.

| Component | Description |
|-----------|-------------|
| Data Lake | A big data architecture responsible for storing all of the raw data required for the ML application. |
| Data Host | A component responsible for extracting and integrating data from all of the data sources in the data lake, validating the data, and preparing a dataset for the model. |
| Feature Store | A big data architecture responsible for storing the extracted features used by the different ML apps. |
| Training Host | A component responsible for training ML models with datasets retrieved from the feature store, performing model validation, and evaluating a model’s performance before its deployment. |
| Model Catalog | A repository that stores all of the ML app resources including the model files, selected features, and models’ metadata. |
| Model | The trained model file, which is produced by feeding training data to the learning algorithm. The model itself is saved in the model catalog and deployed to the serving host. |
| Serving Host | Responsible for deploying a model from the model catalog and providing predictions (e.g., using a REST API). |
| ML-assisted App Host | A component responsible for executing all of the application’s workflow, i.e., receiving the new input and preparing it for the inference stage and activating the appropriate action, according to the model’s output, in the system. |

![Fig. 2: General ML pipeline in ORAN.](image)

![Fig. 3: O-RAN ML Deployment Scenarios.](image)
Refers to the capabilities that are available to the attacker. In the context of AML attacks, a vulnerability refers to the inherent ability to systematically manipulate the input to the ML model.

An individual, group, or state responsible for an incident that impacts, or has the potential to impact, the security or safety of the ML. Threat actors may have different capabilities and resources and may perform different types of attacks.

Refer to the capabilities that are available to the attacker. In the context of AML attackers, we distinguish between access capabilities and knowledge capabilities.

By exploiting vulnerabilities, threats are able to have security impact on the vulnerable assets, e.g., violate the confidentiality of the data used to train a model or tamper with the model’s integrity. Security impact may lead to operational impact.

An act or method that violates the security policy of a system. The third-party applications are deployed as part of the O-RAN’s core functionality and are used to automatically and efficiently manage a system’s resources. The third-party applications can be deployed by every provider that has a 5G-based service they want to provide. Some examples of network management ML-based applications in the O-RAN are: traffic steering (identify the optimal cell for each UE in order to ensure acceptable quality of experience), V2X handover management (optimize handover sequences on the UE level), and resource allocation optimization (predict traffic demands at different times and locations).

The O-RAN ML use cases can be divided into two types: network management applications and third-party applications. The network management applications are deployed as part of the O-RAN’s core functionality and are used to automatically and efficiently manage a system’s resources. The third-party applications can be deployed by every provider that has a 5G-based service they want to provide. Some examples of network management ML-based applications in the O-RAN are:

A. Attacker Model

Each AML attack may require different attacker capabilities in order to be executed. As can be seen in Figure 4, we distinguish between two types of adversarial capabilities: access capabilities (AC) and knowledge capabilities (AK). In addition, we define a partially-ordered set of those capabilities.

1) Access Capabilities (AC): The set of assets/capabilities possessed to the attacker within the O-RAN ML deployment (presented in Figure 2).

Model Access (ACM). An adversary that has access to the ML model used in the specific use case (in the Non-RT RIC/Near-RT RIC).

[ACM1] Score-Based Query Access. An adversary with the ability to query the trained model in the ML-assisted application’s model inference host and obtain the model’s probability vector (the model’s confidence for each class).

[ACM2] Decision-Based Query Access. An adversary with the ability to query the trained model in the Near-RT RIC and obtain the model’s decision (the final classification); i.e., no access to the model’s probability vector.

Data Access (ACD). An adversary with access to the data used in the pipeline of the specific use case (in the Non-RT RIC/Near-RT RIC).

[ACD1] Training Data Access. An adversary with access to the processed dataset in the ML-assisted application’s model’s training host which is used to train the ML-assisted application’s model. In this case, it is assumed that the adversary knows the exact features and samples used to train the model.

[ACD2] Features Data Access. An adversary with access to the raw dataset and the feature transformation functions.

[ACD3] Raw Data Access. An adversary with access to the raw data used by the training host to train the ML-assisted application’s model.

[ACD4] Sensor Data Access. An adversary with the ability to manipulate data sent from a UE (or multiple UEs) that is accessible to the adversary.

2) Attacker’s Knowledge (AK): Information regarding the O-RAN architecture and deployment that is available to the attacker and can be used to more effectively generate AML attacks.

Model Knowledge (AKM). An adversary that knows the exact model used in the ML-assisted application’s pipeline.

[AKM1] Hyperparameter Knowledge. An adversary that knows the exact algorithm and hyperparameters used to train the ML-assisted application’s models, e.g., for an artificial neural network, the hyperparameters include the network architecture, number of epochs used to train the model, learning rate, etc.

[AKM2] Algorithm Knowledge. An adversary that knows the algorithm used to train the ML-assisted ap-

| Entity          | Description                                                                                                                                 |
|-----------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Assets          | The main data, components, processes, and services that comprise an ML production pipeline and should be protected.                             |
| Vulnerability   | In the context of AML attacks, a vulnerability refers to the inherent ability to systematically manipulate the input to the ML model.            |
| Attacker (threat actor) | An individual, group, or state responsible for an incident that impacts, or has the potential to impact, the security or safety of the ML.     |
| Capabilities    | Refers to the capabilities that are available to the attacker.                                                                              |
| Impact (attacker goal) | By exploiting vulnerabilities, threats are able to have security impact on the vulnerable assets, e.g., violate the confidentiality of the data. |
| Attack Technique| An act or method that violates the security policy of a system.                                                                               |

| Threat          | A threat represents a potential violation of a security property, such as integrity, confidentiality, or availability.                         |

TABLE III: The entities included in the threat analysis ontology.
plication’s model but does not know the specific hyperparameters of the model.

**[AKM3] Task Knowledge.** An adversary that has general knowledge of the ML task, including the type of inputs and outputs, e.g., an attacker that knows that the ML pipeline is used to predict the quality of experience (QoE) for a given piece of UE considering the current state of the cells.

**Data Knowledge (AKD).** An adversary that knows the exact data used to train the model in the ML-assisted application’s pipeline.

**[AKD1] Training Data Knowledge.** An adversary that knows all/part of the training data used for training the ML-assisted application’s model (including the specific feature transformations applied on the raw data).

**[AKD2] Features Data Knowledge.** An adversary that knows the raw data and feature transformation functions to the data used to train the model.

**[AKD3] Raw Data Knowledge.** An adversary that knows what raw data is used to train the ML-assisted application’s models (e.g., when a target model is being trained on a public dataset) but is not aware of the specific feature transformations applied to the raw data.

**[AKD4] Data Property Knowledge.** An adversary that knows the statistical properties of the data (data distribution) used to train the ML-assisted application’s models.

**B. O-RAN Threat Actors**

In this section, we describe O-RAN’s threat actors and map them to the relevant adversarial capabilities. The proposed threat model includes two type of threat actors: internal (those that reside within the RAN) and external (those that reside outside the RAN). Table IV summarizes the adversarial capabilities of the various threat actors.

**[A1] O-RAN Software Application Developer.** This threat actor is responsible for developing O-RAN applications, i.e., software code deployed within the O-RAN components, such as the Non-RT RIC (rApp platform), Near-RT RIC (xApp platform), and O-CU/O-DU (yet to be developed). O-RAN applications are implemented as a Kubernetes Pod (currently restricted to have one container) and have access to RAN resources and interfaces via infrastructure utility functions, which provide APIs for reading telemetry data from RAN interfaces, reading from (or writing to) RAN shared storage (SDL), sending and receiving messages, etc. Since this threat actor operates at the application level, we assume that he/she can only compromise the specific application developed by the adversary. Specifically, we assume that this adversary has full control of the host (container) running the compromised component. Thus, the adversarial capabilities of this threat actor depend on the specific application developed (and therefore controlled) by the adversary.

**[A2] O-RAN Software Infrastructure Developer.** Responsible for developing the O-RAN infrastructure, which includes the following core components: (1) scheduling functions (alarm and subscription managers); (2) utility functions (database communication, message routing, rest-full API, and logging); (3) application frameworks (for rapid development of Non-RT RIC, Near-RT RIC, O-CU, and O-DU applications); and (4) interface support, which includes the A1, O1, O2, and E2. Since this threat actor develops the core infrastructure, we assume that he/she can compromise any application deployed within the infrastructure. Specifically, we...
assume that this adversary has full control over the compromised infrastructure and as a result, full control of the applications that use that software infrastructure. The adversarial capabilities of this threat actor depend on the location of the compromised infrastructure within the O-RAN (i.e., Non-RT RIC, Near-RT RIC, and O-CU/O-DU) and the deployment scenario (which is based on the learning task and latency constraint).

[A3] Containerization Software Infrastructure Provider. Provides virtualized/containerization software infrastructure such as the Kubernetes and Docker infrastructure. We assume that this threat actor can compromise any application (container) deployed within the compromised infrastructure. Specifically, we assume that this adversary has full control of the compromised infrastructure and as a result, full control of the containers running on the compromised infrastructure. To simplify the assessment, we assume that all O-RAN containerization infrastructures are provided by the same provider; thus, the adversarial capabilities of this threat actor are not dependent on the deployment scenario.

[A4] Hardware Infrastructure Provider. This threat actor provides the hardware infrastructure used in the O-RAN. We assume that this threat actor can compromise any software running on the compromised hardware infrastructure. Specifically, we assume that this adversary has full control of the compromised hardware and as a result, full control of the software running on the compromised infrastructure. To simplify the assessment, we assume that all O-RAN components are provided by the same provider; thus, the adversarial capabilities of this threat actor are not dependent on the deployment scenario.

[A5] User Equipment (UE). User equipment that is connected to the O-RAN. We assume that this threat actor can change its own behavior (i.e., is able to manipulate sensor data) in order to attack machine learning models deployed within the O-RAN. In addition we assume that this threat actor has decisions-based query access to the deployed model, that is, the adversary is affected by model’s decisions.

C. Attacker’s Goal

[AG1] Tampering. This type of threat is associated with malicious activities that would compromise the integrity of the O-RAN system.

[AG2] Denial of Service. This type of threat is associated with malicious activities that would compromise the availability of the O-RAN system. This goal can be achieved by causing, for example, the QoE model to make an incorrect prediction and infer that a specific cell is better than all of the others for all UEs; therefore, the model will allocate all of the users to the same cell.

[AG3] Information Disclosure. This type of threat is associated with malicious activities that would compromise the privacy of the data/models used in the O-RAN.

VI. Threat Analysis

We performed a thorough analysis of the AML threats in O-RAN. Following is a brief description of the main AML threat categories.

[T1] Evasion. An adversary that causes the ML model to provide incorrect outputs for a specific input, e.g., causing the QoE model to classify an excellent signal as a poor signal. This threat mainly compromises the integrity of the machine learning model.

[T2] ML Model Corruption. An adversary that causes the ML model to make incorrect decisions for targeted samples, e.g., causing the QoE model to allocate all UE to a certain cell. This threat can compromise both the integrity and availability of the ML model.

[T3] Membership Inference. An adversary that attempts to extract information regarding the existence of a given input sample in the model’s training set, e.g., exposing the fact that certain UE was connected to a certain cellular cell. This threat compromises the privacy of the ML model.

[T4] Data Property Inference. An adversary that attempts to extract information from the ML model in order to learn about general properties of the model’s training dataset (such as the feature distribution or input types), e.g., exposing the average quality of service of various UE or cellular cells. This threat compromises the privacy of the ML model.

[T5] Data Reconstruction (theft). An adversary that causes the ML model to leak information in such a way that some of the data samples used to train the model are exposed, e.g., exposing timeframes in which UE results in a poor QoE. This threat compromises the privacy of the ML model.

[T6] Model Extraction. An adversary that attempts to extract information about the model (usually by querying the model) in order to train a replica of the model, e.g., replicating the model used for QoE classification. This threat compromises the privacy of the ML model.

[T7] Resource Exhaustion. An adversary that causes the the ML model to use more resources at inference time, e.g., increasing the latency of the QoE model when classifying targeted examples. This threat compromises the availability of the machine learning model.

We review various attack families against ML systems. For each attack family, we provide a brief description of the attack method, identify the adversarial capabilities required to successfully execute the attack, and map these capabilities to the relevant threat actors and impact.

We also present a taxonomy of AML attack families (see Figure 5) which classifies each attack family according to the following three criteria:

1) Threat category: The threat materialized by the attack (i.e., corruption, evasion, inference, extraction, and resource exhaustion).

2) General threat model: The general threat model classification, which is based on the privileges required
A. Traffic Steering Overview

In this section, we demonstrate the applicability of an AML attack on the traffic steering use case. The demonstration is based on the O-RAN SC’s third open software release, “Cherry,” which implements the Near-RT RIC—a software-based near-real-time platform for hosting and running microservice applications (xApps) on Linux/Kubernetes. The Near-RT RIC platform provides the application development platform (xApp), the design and implementation of the open A1/E2 communication interfaces, and the development of cellular network management infrastructure.

The traffic steering task is illustrated in Figure 6. The UE is located within the reception range of Cells A, B, and C and can be connected by each of these cells. The network provider needs to make a decision regarding which cell the UE should be connected to so that the UE has an acceptable quality of experience (QoE) without compromising the QoE of other UEs. This challenge is addressed by the traffic steering ML-based application.

The TS process is illustrated in Figure 6: The KPI monitor (KPIMON) xApp continuously collects data from the O-CUs and O-DUs, computes UE and cell metrics (i.e., features), and stores them in the Near-RT RIC for other xApps’ usage (step 1). The Anomaly detection (AD) xApp, which is scheduled to run every 10 ms, detects UE with an anomalous QoE (step 2). Anomaly detection is performed based on the UE metrics extracted by the KPIMON xApp and stored in the Near-RT RIC. This list of anomalies is sent over the remote message router (RMR) API to the traffic steering (TS) xApp for reallocation of the anomalous UE (step 3). Then, the QoS prediction (QP) xApp is called by the TS xApp, and for each anomalous UE, it receives the UE and cell metrics and predicts the QoS of the UE in a given cell (steps 4 and 5). Finally, based on the predictions provided by the QP xApp and the given A1 policy (which includes configuration information for the ML-assisted application, e.g., the threshold for cell reallocation, in traffic steering), the TS xApp decides whether to allocate anomalous UE to a new cell (steps 6 and 7). The deployment of the various components of the TS use case within the O-RAN framework is presented in Figure 1.

B. Attack Scenario

While there are various AML attacks that can be performed in the TS use case, we demonstrate an attack in which the threat actor is a malicious UE. Based on the attacker model described in Section V, we assume that the attacker has the following adversarial capabilities: (a) Sensor data access—the adversary can manipulate the behavior (data) of its own UE; (b) Decision-based query access—the adversary knows its current serving cell; and (c) Task knowledge—the adversary knows the traffic steering task’s input and goal. The goal of the adversary is to receive a high QoE while spoofing KPIs such that the signal is classified as poor by the ML application used for QoE prediction. Such an attack may result in alert fatigue (many alerts about UEs with anomalous QoE) and in the exhaustion of resources (UE handover from one cell to another is a resource-consuming operation). In this attack scenario, the adversary generates a crafted signal by manipulating its own behavior; this manipulation is initiated by an AML attack. The signal parameters are propagated through the O-RU, O-DU, and O-CU, and the KPIMON xApp extracts KPIs from the manipulated signal. The AD xApp and QP xApp produce the estimated QoE for each neighbor cell and send that information to the traffic steering xApp which updates the serving cell accordingly. The adversary receives the cell update status and updates the crafted signal. This process is repeated until the cell serving the UE is changed.
| Threat Category | Attack Family | Description |
|-----------------|---------------|-------------|
| Evasion         | Gradient-based evasion (white-box) | The adversary manipulates an input sample in such a way that the classification loss is maximized. The specific manipulation is determined by calculating the gradients of the classification loss with respect to the input sample [15], [23], [6]. |
|                  | Query-based evasion (interactive-black box) | The adversary interactively queries the model and estimates the gradients of the classification loss with respect to the input sample, based on the classification results [9], [8]. |
|                  | Transferability-based evasion (complete black-box) | Exploits the transferability property of ML models [33], [9], [15], i.e., adversarial examples that affect one model can often affect other models. To exploit this property, the adversary creates a surrogate model by training a learning algorithm on a reference dataset and generates adversarial examples by executing white-box gradient-based attacks on the surrogate model. Then, the adversary uses the adversarial examples to attack the target model. |
| Model Corruption | Gradient-based poisoning (white-box) | The adversary manipulates a small number of training samples in such a way that the classification loss of some other set of samples targeted by the attacker is maximized. The specific manipulation is calculated by solving, using gradient-optimization techniques, a bi-level optimization problem [21], [27], [18]. |
|                  | Transferability-based poisoning (black-box). | Similar to gradient-based poisoning attacks, manipulates a small number of training samples in such a way that the classification loss of some other set of samples targeted by the attacker is maximized. However, in contrast to gradient-based poisoning attacks, the gradients are calculated using a surrogate model [4], [23], [13]. |
| Membership Inference | Gradient-based inference (white-box). | The adversary calculates the gradients of the loss with respect to all parameters and analyzes the distribution of these gradients on members of the training data, versus non-members [30]. The rationale behind this attack is the fact that the gradients of training examples are pushed to zero during the training procedure. |
|                  | Query-based inference (black-box). | The adversary utilizes reference data to train multiple shadow models, which are meant to behave similarly to the target model, note that the adversary knows which record was included in the training dataset of each shadow model. Then, the adversary trains a supervised machine learning model that can distinguish between members of training data, versus non-members (attack model). Finally, given a record, the adversary queries the target model and passes the label, along with the returned vector of probabilities, to the attack model for classification [30], [3], [14], [38]. |
| Data Reconstruction | Gradient-based data reconstruction (white-box). | The adversary reconstructs the model by making use of gradient-based optimization methods. That is, the adversary tries to find the optimal data for a given class [12], [23], [24], [25], [19], [20]. |
|                  | Query-based data reconstruction (black-box). | The adversary reconstructs the model by training a second model that acts as the inverse of the target model [41], [14], [10], [29]. |
| Model Extraction | Gradient-based resource exhaustion (white-box) | The adversary uses a genetic algorithm for inputs that increase activation values of the model across all of the layers simultaneously. High activation values prevent hardware optimization and therefore increase latency [37]. |
|                  | Query-based resource exhaustion (interactive black-box) | The adversary searches (using gradient optimization method) for inputs that increase model’s latency. In contrast to gradient-based method, this method does not require access to the model’s parameters [37]. |
|                  | Transferability-based resource exhaustion (complete black-box) | In this type of attack, the adversary creates a surrogate model and searches (using a genetic algorithm or gradient-based optimization) for inputs that increase models’ latency. |

**TABLE V: Adversarial machine learning attack families.**

### C. Attack Implementation

The TS use case in the Cherry version has the following limitations: (i) the SMO logic is not implemented, and therefore the AD xApp and QP xApp in the Near-RT RIC implement the whole ML workflow (i.e., data processing, training, prediction); (ii) the QP xApp is not implemented; (iii) the anomaly detection process (the AD xApp) is implemented in two phases: first, a signal classification model is used to predict for a given UE the QoE category of a given signal (which can be excellent, good, average, or poor) and then, a naive rule-based approach is used for selecting the anomalous UEs; (iv) only an offline implementation of the use case is available, i.e., the data is not dynamic, and only a static dataset for training and evaluation is available.

Given the above limitations, the implemented attack focused on the signal classification model (implemented as part of the AD xApp):

**Task:** Predict for a given UE the QoE category of a signal.

**Training set:** Collected using a simulator which was created specifically to simulate the activity of multiple UEs in a predefined geographical area.

**Features:** The KPIMON xApp extracts two feature groups: *UE metrics* that include: the UE ID and serving cell ID, PDCP report timestamp, PDCP aggregation period, UE PDCP downlink/uplink, resource block (PRB) report timestamp, PRB aggregation period, UE PRB downlink/uplink ratios, serving cell report timestamp, reference signal received power (RSRP), reference signal received quality (RSRQ), and signal-to-noise ratio (SNR); and, *Cell metrics* that include: the cell ID, PDCP report timestamp, PDCP aggregation period, PDCP downlink/uplink as the PCDP, PRB report timestamp, PRB aggregation period, and PRB downlink/uplink ratios.

**Labels:** The true labels (i.e., QoE categories) of the signals were assigned using an expert-based procedure which defines KPI thresholds for each category.

**Algorithm:** Random Forest model.

For the attack implementation we select HopSkipJump [8], a query-based evasion attack technique. The attack begins by sampling two signals from the training set: a poor signal and an excellent signal. Those signals are the *initial sample* and *target sample*, which are required for the execution of the HopSkipJump attack. In each step of the attack, the adversary (1) performs a binary search between the initial signal and the target signal; (2) adjusts the resulting sample based on the gradient with respect to the boundary.

Figure 7 illustrates the classifier’s decision boundary, and presents a single case where we applied the HopSkipJump attack. The illustration was created by monotonically sampling the input space of the classifier (UMAP was used for dimensionality reduction). As can be seen, the decision boundaries of the different categories overlap. This observation demonstrates the feasibility of performing an evasion attack on the RF.
| Attack Family | Attack Technique Exploiting... | Threat Model Knowledge | Threat Model Access | Threat Model Impact | Threat Actor ACM | Threat Actor AKM | Threat Actor ACD | Threat Actor ACM | Threat Model Data Collection | Threat Model Data Theft and Data Tampering | Threat Model Denial of Service | Threat Model Information Disclosure |
|---------------|--------------------------------|------------------------|--------------------|--------------------|-----------------|-----------------|-----------------|-----------------|-------------------------------|--------------------------------------|-------------------------------|----------------------------------|
| Gradient-based | evasion attacks | training data and hyperparameter knowledge | ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◦ ◆ AML

Table VI: Adversarial machine learning attack techniques and threat actors.

model. We also present the path from the initial sample (a poor signal) to the adversarial sample. As can be seen, the adversarial example is classified as a poor signal but labeled (based on the expert thresholds) as an excellent signal. This process can be repeated to generate many adversarial examples.

VIII. CONCLUSIONS

We present a systematic AML threat analysis of the O-RAN. We also demonstrate the applicability of an AML attack on the traffic steering use case implemented in the O-RAN reference implementation. In future work, we intend to develop an extension to the MulVAL attack-framework to incorporate the representation of cyberattacks for ML applications in the O-RAN. We also plan to propose and evaluate a method for suggesting the optimal countermeasure deployment to address the identified risks.
Fig. 7: Demonstrating an attack strategy using the Hop-SkipJump attack technique.

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