kTRACKER: Passively Tracking KRACK using ML Model

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ABSTRACT

Recently, a number of attacks have been demonstrated (like key reinstallation attack, called KRACK) on WPA2 protocol suite in Wi-Fi WLAN. In this paper, we design and implement a system, called kTRACKER, to passively detect anomalies in the handshake of Wi-Fi security protocols, in particular WPA2, between a client and an access point using COTS radios. A state machine model is implemented to detect KRACK attack by passively monitoring multiple wireless channels. In particular, we perform deep packet inspection and develop a grouping algorithm to group Wi-Fi handshake packets to identify the symptoms of the KRACK in specific stages of a handshake session. Our implementation of kTRACKER does not require any modification to the firmware of the supplicant i.e., client or the authenticator i.e., access point or the COTS devices, our system just needs to be in the accessible range from clients and access points. We use a publicly available dataset for performance analysis of kTRACKER. We employ gradient boosting-based supervised machine learning models, and show that an accuracy around 93.39% and a false positive rate of 5.08% can be achieved using kTRACKER.

KEYWORDS

Wi-Fi, WPA2, KRACK, Ensemble model

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1 INTRODUCTION

Recently, a number of attacks has been reported that targets authentication, key negotiation, and encryption schemes in the WPA2 protocol suite, e.g., the WiFi key re-installation attack (KRACK) [8], and active and passive eavesdropping attacks on Wi-Fi [2].

While some of those attacks could potentially be prevented by firmware updates of the involved devices, such updates are often not possible for a variety of reasons, including but not limited to, cost-benefit trade-offs to end users. A number of wireless intrusion detection systems (WIDS) have been proposed to address MAC-layer misbehaviour[1, 7], but those systems are focused on detecting specific individual malicious packets that indicate the misbehaviour of a set of devices/users in the neighborhood. Unfortunately, the attacks that manipulate the security handshake in wireless environment cannot be detected by the existing anomaly detection systems, we claim that the detection of such attacks requires a stateful observation of the packets being exchanged on (multiple) wireless channels.

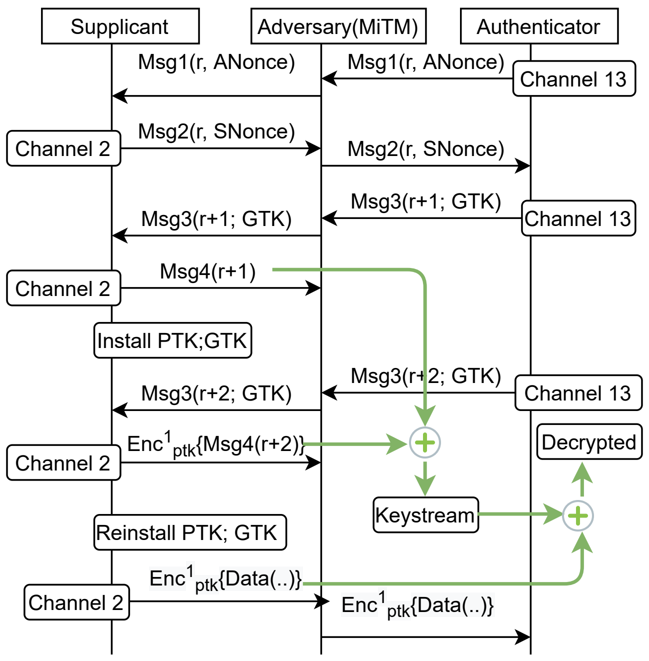

Figure 1: KRACK Attack

In this work, we aim to design and develop a tool that can passively capture Wi-Fi packets pertaining to connection establishment rather than data transfers and deep inspect the packets to look for anomalies in WPA2 handshakes. Secure connection in Wi-Fi goes through a well-defined sequence of probing, authenticating, associating, and handshaking (i.e., performing a 4-way handshake) that can be captured by sniffer module of kTRACKER and pass as an input to state machine to detect anomalies (presence of KRACK trail) in the establishment of security connection between a pair of an authenticator and a supplicant. We leverage this stateful property of secure connection establishment and check if the state machine executes through appropriate states in estimated time frame, and any violation of the state machine potentially indicates an anomaly.

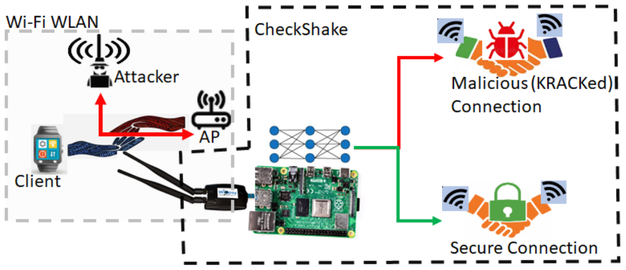

Figure 2: System model

2 TRACKING KRACK IN HANDSHAKE

System model of kTRACKER is depicted in Figure 2. A legitimate AP, like a Dlink Wi-Fi router, is communicating with a client and the AP is configured to use WPA2 protocol suite to secure the communication. An attacker is physically placed within the coverage area of the AP. kTRACKER is capable of sniffing on more than one Wi-Fi channel.

2.1 KRACK Characterization

KRACK attack, [8], exploits a weakness of 18-year-old WPA/WPA2 Wi-Fi security protocol. Recently, in [4], Wi-Fi traffic containing KRACK attack has been published for public use and further research. In this paper, for the first time, we inspect this trace in detail and identify the handshakes in the trace showing the symptoms of such an attack, and if not, then we specify the violated preconditions if any. Figure 1 shows the arrangement of KRACK attack, where the adversary is a channel-based MitM. The adversary impersonates the supplicant on channel 13 that the legitimate AP (Authenticator) is active, and it impersonates the authenticator on channel 2 on which the supplicant is already tricked to operate on.

2.2 Design of kTRACKER

This section describes in detail the architecture of kTRACKER that we propose in this paper for the first time. kTRACKER contains six different modules and each module performs a well-defined task. Figure 3 shows an architectural view of kTRACKER. Module ①, sniffs the Wi-Fi packets, Module ② performs deep inspection of the packets across different phases of Wi-Fi connection establishment, like authentication, association, 4-way handshake, Module ③ group different packets from *Auth* request to handshake message *m4* to form different session. Module ④ labels the Benign and anomalous group by looking at the KRACK trail i.e. repetition of *m3* on legitimate and fake channel and absence of *m4* on legitimate channel. Finally in Module ⑤ ML model is employed and trained using label data and tested for unkown labels.

2.3 Session Grouping Module

The Grouping Module takes feature vectors sequentially as input and segregates the handshake sessions following the Mealy State Machine (MSM) model shown in Figure 4. Packets corresponding to one handshake session (i.e. packets from authentication to ideally *m4*) are put in a single group. The output g_1 (resp. g_2) in each transition in MSM indicates the current (resp. new) group of packets.

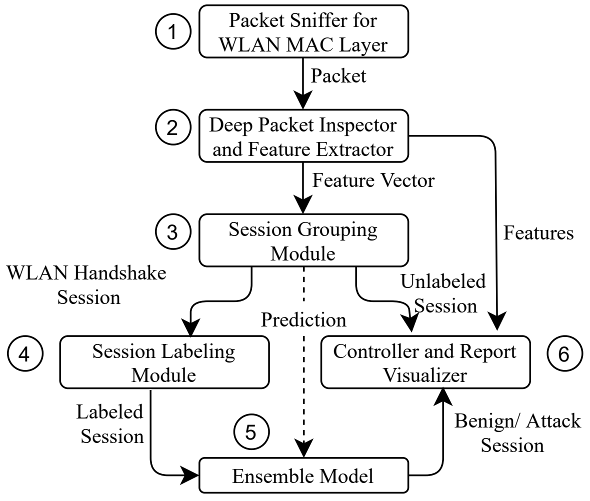

Figure 3: Different Modules of the kTRACKER

The MSM starts with q_0 state when first *auth* request packet creates a handshake session indicated by g_1 as output of the transition. On successful authentication, client sends the *assoc* request to AP and the machine transits to q_2 state keeping the packet in the same group indicated by the transition output g_1. It waits in this state till repeated *assoc* (request or response) packets are seen. The machine moves to q_0 from q_1 if an *auth* request is observed, creating a new group indicated by the transition output g_2. The machine proceeds to q_2 from q_1 on seeing *m1* without creating any new group and remains in this state till *m1* is repeated. If an *auth* request/response is seen in q_2, then this packet is assigned to a new group and the machine moves to q_0 state. Alternatively, if any *assoc* packet is seen then the state changes to q_1 keeping the packets in the same group. In ideal case, the state changes to q_3 from q_2, if *m2* is observed. In state q_3, if an *auth* request is seen, then a new group is created and the state changes to q_0, however the state changes to q_1 or q_2 on seeing an *assoc* packet or *m1* respectively. In ideal case, the state changes to q_4 from q_3, if m_3 is seen. A new group is created only if an *auth* packet is seen in this state and the machine transits to q_0.

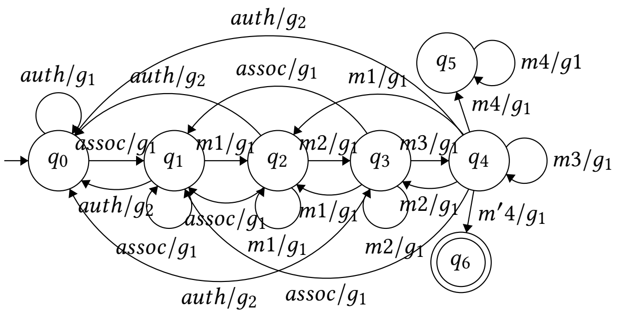

Figure 4: State Machine for Grouping Algorithm

Alternately, the state changes to q_1, q_2 or q_3, if *assoc* packet or m_1 or m_2 is seen respectively without creating any new group of packets. Finally, the state changes to q_5 from q_4, if m_4 is seen on fake channel and in ideal case changes to q_6, if m_4 i.e., $m'4$ (shown in state machine) is seen on legitimate channel and this indicates a successful and secure handshake.

Algorithm 1: Grouping Algorithm, uses Python syntax.

```
Input: f_list = List of Features extracted from EAPOL frame
Output: Grouping of different handshakes
group_dict = {count:[] for count in num_of_group}
for pkt in packet[f_list] do
    field_values = [], set_re=0, retransmit=0, group=[]
    count=0,layer_type = type(pkt[f_list].payload)
    if (isAuth(pkt)) then
        count = count+1, group.append(count)/* new group */
    if (isAssoc(pkt)) or (isM1(pkt)) or (isM2(pkt)) then
        group.append(count),
    if (isM3(pkt)) then
        if (set_re == 0) then
            group.append(count), set_re = 1
        if (set_re == 1) then
            group.append("remsg3"+str(count))
            retransmit = retransmit+1, set_re = 1
    if (isM4(pkt)) then
        group.append(count), count = count+1, set_re=0
    field_values.append(layer_type).fields[field]
      group_dict[count].append(pkt)
```

Alternately, the state reaches to q_0 if *auth* packet is seen and a new group is created. Otherwise, the state transits to q_1, q_2, q_3, or q_4 state if *assoc* packet, *m1*, *m2* or *m3* is seen respectively without creating any new group. The state machine in Figure 4 is implemented using Algorithm 1 in Module ③. We use simple functions to check if a packet, pkt, is of desired type, e.g., `isAuth(pkt)` function returns *true* if pkt.type =0 and pkt.subtype = 11. Similarly, `isAssoc(pkt)`, `isM1(pkt)`, `isM2(pkt)`, `isM3(pkt)`, and `isM4(pkt)` functions return true if pkt is identified as *(re)assoc* request or response packet, *m1*, *m2*, *m3* or *m4* packet in 4-way handshake respectively.

2.4 Performance of kTRACKER

We illustrated the evaluation metrics in Table 1 which indicates the performance of classifying benign and anomalous group (existence of KRACK trail i.e. repetition of *m3* in legitimate and fake channel).

Table 1: Classification performance and FPR is false positive rate.

[Classifier] / [Metrics]	XGboost	LightGBM	Catboost
Precision	87.76	87.68	91.04
Recall	87.12	87.12	90.15
F1 Score	87.15	87.15	90.17
Accuracy	87.12	87.12	90.15
FPR	8.47	8.47	5.08

we observe that a maximum accuracy of 93.39% and weighted average accuracy of 90.15% for binary classification can be achieved with Catboost. The same in both LightGBM and XGboost is fixed at 87.12%. Though these initial results are exciting, in-depth feature engineering, better ML model selection and model validation are evident to reduce FPR, for instance, and we consider this as a part of our future exploration.

3 RELATED WORK

Cremers et al. in [5], used automated security analysis tool, called *Tamarin prover*, to model the behavior of the protocols in presence of different attacks, and proposed security patches for attacks like KRACK. In [6], Yi Li et al. proposed a software-defined network-based framework which replicates the behaviour of a client and an AP and SDN controller is responsible for detecting and mitigating the attacks like KRACK by using duplicated *m3*. In [3], Urbi et al. have proposed to create mutually authenticated APs and supplicants by using Physically Unclonable Functions (PUFs) and hence eliminate the possibility of creating a rogue AP which is one of the preconditions of launching KRACK attack. Our work is different from the existing approaches as it passively detects the KRACK attacks, kTRACKER does not require any special hardware device for its functioning, proposed solution looks for specific KRACK trails and train the ML model to classify the characteristics of KRACK, the ML model once trained can be deployed to any Wi-Fi setup that makes it scalable.

4 CONCLUSION

kTRACKER use deep packet inspection to group handshake packets and detect KRACK. The final goal of this line of work is to develop a fully automated tool for detection of anomaly in Wi-Fi handshakes, and in particular KRACK.

5 ACKNOWLEDGMENT

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