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Key-Recovery Attacks Prevention in Keyed Anomaly Detection System

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ABSTRACT:

Most anomaly detection systems rely on machine learning algorithms to derive a model of normality that is later used to detect suspicious events. Some works conducted over the last years have pointed out that such algorithms are generally susceptible to deception, notably in the form of attacks carefully constructed to evade detection. Various learning schemes have been proposed to overcome this weakness. One such system is KIDS (Keyed IDS), introduced at DIMVA'10. KIDS' core idea is akin to the functioning of some cryptographic primitives, namely to introduce a secret element (the key) into the scheme so that some operations are infeasible without knowing it. In KIDS the learned model and the computation of the anomaly score are both key-dependent, a fact which presumably prevents an attacker from creating evasion attacks. In this work System that recovering the key is extremely simple provided that the attacker can interact with KIDS and get feedback about probing requests. System realistic attacks for two different adversarial settings and show that recovering the key requires only a small amount of queries, which indicates that KIDS does not meet the claimed security properties. System revisit KIDS' central idea and provide heuristic arguments about its suitability and limitations.

KEYWORDS: Upload file & generate Key, Request for key, Access File.

I. INTRODUCTION

Many computer security problems can be essentially reduced to separating malicious from non-malicious activities. This is, for example, the case of spam filtering, intrusion detection, or the identification of fraudulent behavior. But, in general, defining in a precise and computationally

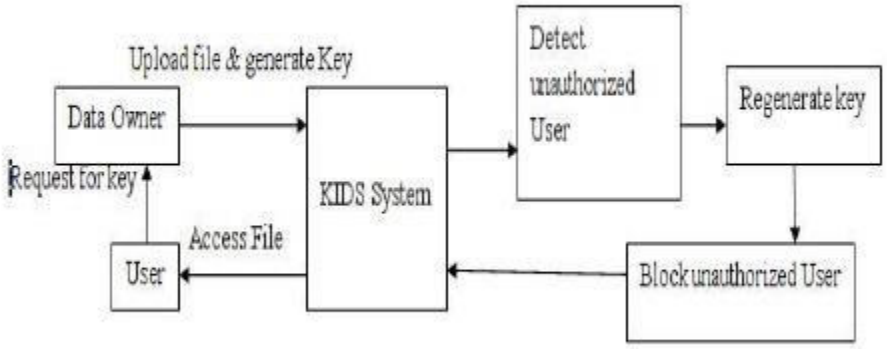
useful way what is harmless or what is offensive is often too complex. To overcome these difficulties, most solutions to such problems have traditionally adopted a machine-learning approach, notably through the use of classifiers to automatically derive models of (good and/or bad) behavior that are later used to recognize the occurrence of potentially dangerous events. Recent work has accurately pointed out that security problems differ from other application domains of machine learning in, at least, one fundamental feature: the presence of an adversary who can strategically play against the algorithm to accomplish his goals. Thus for example, one major objective for the attacker is to avoid detection. Evasion attacks exploit weaknesses in the underlying classifiers, which are often unable to identify a malicious sample that has been conveniently modified so as to look normal. Examples of such attacks abound. For instance, spammers regularly obfuscate their emails in various ways to avoid detection, e.g., by modifying words that are usually found in spam, or by including a large number of words that do not. Similarly, malware and other pieces of attack code can be carefully adapted so as to evade intrusion detection systems (IDS) without compromising the functionality of the attack. A few detection schemes proposed over the last few years have attempted to incorporate defenses against evasion attacks. One such system is keyed intrusion detection system (KIDS), relative positions in the payload. KIDS' core idea to impede evasion attacks is to incorporate the notion of a "key", this being a secret element used to determine how classification features are extracted from the payload. The security argument here is simple: even though the learning and testing algorithms are public, an adversary who is not in possession of the key will not know exactly how a request will be processed and, consequently, will not be able to design attacks that thwart detection. Strictly speaking, KIDS' idea of "learning with a secret" is not entirely new: Wang et al. introduced in Anagram, another payload-based anomaly detection system that addresses the evasion problem in quite a similar manner. System distinguish here between two broad classes of classifiers that use a key. In the first group, that term randomized classifiers; the classifier is entirely public (or equivalently, is trained with public information only). However, in detection mode some parameters (the key) are randomly chosen every time an instance has to be classified, thus making uncertain for the attacker how the instance will be processed. Note that, in this case, the same instance will be processed differently every time if

the key is randomly chosen. System emphasize that randomization can also be applied at training time, although it may only be sufficiently effective when used during testing, at least as far as evasion attacks are concerned. KIDS belong to a second group, that System call keyed classifiers. In this case, there is one secret and persistent key that is used during a period of time, possibly because changing the key implies retraining the classifier. If Kickoffs' principle is to be followed, it must be assumed that the security of the scheme depends solely on the secrecy of the key and the procedure used to generate it. Anagram can be used both as randomized and as a keyed classifier, depending on the variant used.

II. RELATED WORK

The problem of computing optimal strategies to modify an attack so that it evades detection by a Bayes classifier. They formulate the problem in game-theoretic terms, where each modification made to an instance comes at a price, and successful detection and evasion have measurable utilities to the classifier and the adversary, respectively. The authors study how to detect such optimally modified instances by adapting the decision surface of the classifier, and also discuss how the adversary might react to this. The setting used in assumes an adversary with full knowledge of the classifier to be evaded. Shortly after, how evasion can be done when such information is unavailable. They formulate the adversarial classifier reverse engineering problem (ACRE) as the task of learning sufficient information about a classifier to construct attacks, instead of looking for optimal strategies. The authors use a membership oracle as implicit adversarial model: the attacker is given the opportunity to query the classifier with any chosen instance to determine whether it is labeled as malicious or not. Consequently, a reasonable objective is to find in-stances that evade detection with an affordable number of queries. A classifier is said to be ACRE learnable if there exists an algorithm that finds a minimal-cost in-stance evading detection using only polynomial many queries. Similarly, a classifier is ACRE k-learnable if the cost is not minimal but bounded by k. Among the results given, it is proved that linear classifiers with continuous features are ACRE k-learnable under linear cost functions. Therefore, these classifiers should not be used in adversarial environments. Subsequent work by

generalizes these results to convex-inducing classifiers, showing that it is generally not necessary to reverse engineer the decision boundary to construct undetected instances of near-minimal cost. For the some open problems and challenges related to the classifier evasion problem. More generally, some additional works have revisited the role of machine learning in security applications, with particular emphasis on anomaly detection.



III. PROPOSED ALGORITHM

The attacks are extremely efficient, showing that it is reasonably easy for an attacker to recover the key in any of the two settings discussed. System such a lack of security reveals that schemes like kids were simply not designed to prevent key recovery attacks. However, in this paper system argued that resistance against such attacks is essential to any classifier that attempts to impede evasion by relying on a secret piece of information. System provided discussion on this and other open questions in the hope of stimulating further research in this area. The attacks here presented could be prevented by introducing a number of ad hoc counter measures the system, such as limiting the maximum length of words and payloads, or including such quantities as classification features. I suspect, however, that these variants may still be vulnerable to other attacks. Thus, our recommendation for future designs is to base decisions on robust principles rather than particular fixes.

V.CONCLUSION AND FUTURE WORK

In this paper system analyzed the strength of KIDS against key-recovery attacks. System presented Key-recovery attacks according to two adversarial settings, depending on the feedback given by KIDS to probing queries. The focus in this work has been on recovering the key through efficient procedures, demonstrating that the classification process leaks information about it that can be leveraged by an attacker. However, the ultimate goal is to evade the system, and System just assumed that knowing the key is essential to craft an attack that evades detection or, at least, that significantly facilitates the process. It remains to be seen whether a keyed classifier such as KIDS can be just evaded without explicitly recovering the key. If the answer is in the affirmative, then the key does not ensure resistance against evasion.

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