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Security Pattern Classifiers for Adversarial Applications

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Abstract: *Pattern classification systems are commonly used in adversarial applications, like biometric authentication, network intrusion detection, and spam filtering, in which data can be purposely manipulated by humans to undermine their operation. As this adversarial scenario is not taken into account by classical design methods, pattern classification systems may exhibit vulnerabilities, whose exploitation may severely affect their performance, and consequently limit their practical utility. In this paper, we address one of the main open issues: evaluating at design phase the security of pattern classifiers, namely, the performance degradation under potential attacks they may incur during operation. We propose a framework for empirical evaluation of classifier security that formalizes and generalizes the main ideas proposed in the literature, and give examples of its use in three real applications. Reported results show that security evaluation can provide a more complete understanding of the classifier's behavior in adversarial environments, and lead to better design choices*

Keywords: Data Mining; Java Technology; UML Diagrams; Data Flow Diagram;

1.INTRODUCTION:

PATTERN classification systems based on machine learn-ing algorithms are commonly used in security-related applications like biometric authentication, network intrusion detection, and spam filtering, to discriminate between a "legitimate" and a "malicious" pattern class (e.g., legitimate and spam emails). Contrary to traditional ones, these applications have an intrinsic adversarial nature since the input data can be purposely manipulated by an intelligent and adaptive adversary to undermine classifier operation. This often gives rise to an arms race between the adversary and the classifier designer. Well known examples of attacks against pattern classifiers are submitting a fake biometric trait to a biometric authentication system (spoofing attack) [1], [2]; modifying network packets belonging to intrusive traffic to evade intrusion detection systems (IDSs) [3]; manipulating the content of spam emails to get them past spam filters (e.g., by misspelling common spam words to avoid their detection) [4], [5], [6]. Adversarial scenarios can also occur in intelligent data M analysis [7] and information retrieval [8]; e.g., a malicious webmaster may manipulate search engine rankings to artificially promote her1 website. It is now acknowledged that, since pattern classification systems based on classical theory and design methods [9] do not take into account adversarial settings, they exhibit vulnerabilities to several po-tential attacks, allowing adversaries to undermine their effectiveness A systematic and unified treatment of this issue is thus needed to allow the trusted adoption of pat-tern classifiers in adversarial environments, starting from the theoretical foundations up to novel design methods, extending the classical design cycle of [9].

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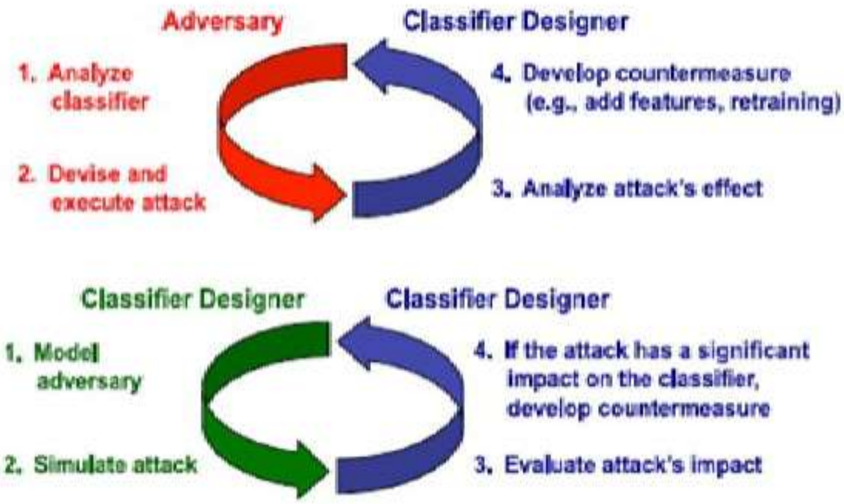

Fig. 1. A conceptual representation of the arms race in adversarial classification. Left: the classical "reactive" arms race.

The designer reacts to the attack by analyzing the attack's effects and developing countermeasures. Right: the "proactive" arms race advocated in this paper. The designer tries to anticipate the adversary by simulating potential attacks, evaluating their effects, and developing countermeasures if necessary In particular, three main open issues can be identified: (i) analyzing the vulnerabilities of classification algorithms, and the corresponding attacks (ii) developing novel methods to assess classifier security against these attacks, which is not possible using classical performance evaluation methods (iii) developing novel design methods to guarantee classifier security in adversarial environments Although this emerging field is attracting growing interest, the above issues have only been sparsely addressed under different perspectives and to a limited extent. Most of the work has focused on application-specific issues related to spam filtering and network intrusion detection while only a few theoretical models of adversarial classification problems have been proposed in the machine learning literature however, they do not yet provide practical guidelines and tools for designers of pattern recognition systems. Besides introducing these issues to the pattern recognition research community, in this work we address issues (i) and (ii) above by developing a framework for the empirical evaluation of classifier security at design phase that extends the model selection and performance evaluation steps of the classical design cycle of [9].

2.SPAM FILTERING:

Assume that a classifier has to discriminate between legitimate and spam emails on the basis of their textual content, and that the bag-of-words feature representation has been chosen, with binary features denoting the occurrence of a given set of words. This kind of classifier has been considered by several authors and it is included in several real spam filters.7 In this example, we focus on model selection. We assume that the designer wants to choose between a support vector machine (SVM) with a linear kernel, and a logistic regression (LR) linear classifier. He also wants to choose a

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feature subset, among all the words occurring in training emails.

A set D of legitimate and spam emails is available for this purpose. We assume that the designer wants to evaluate not only classifier accuracy in the absence of attacks, as in the classical design scenario, but also its security against the well-known bad word obfuscation (BWO) and good word insertion (GWI) attacks. They consist of modifying spam emails by inserting "good words" that are likely to appear in legitimate emails, and by obfuscating "bad words" that are typically present in spam [6]. The attack scenario can be modeled as follows.
Attack scenario. Goal. The adversary aims at maxi-mizing the percentage of spam emails misclassified as legitimate, which is an indiscriminate integrity violation. Knowledge. As in [6], [10], the adversary is assumed to have perfect knowledge of the classifier, i.e.,: (k.ii) the feature set, (k.iii) the kind of decision function, and (k.iv) its parameters (the weight assigned to each feature, and the decision threshold). Assumptions on the knowledge of (k.i) the training data and (k.v) feedback from the clas-sifier are not relevant in this case, as they do not provide any additional information. Capability. We assume that the adversary: (c.i) is only able to influence testing data (exploratory attack); (c.ii) cannot modify the class pri-ors; (c.iii) can manipulate each malicious sample, but no legitimate ones; (c.iv) can manipulate any feature value (i.e., she can insert or obfuscate any word), but up to a maximum number nmax of features in each spam email [6], [10].

This allows us to evaluate how gracefully the classifier performance degrades as an increasing number of features is modified, by repeating the evaluation for increasing values of nmax. Attack strategy. Without loss of general-ity, let us further assume that x is classified as legitimate if gðxÞ ¼ Pn i¼1 wixi þ w0 < 0, where gð_Þ is the discriminant function of the classifier, n is the feature set size, xi 2 f0; 1g are the feature values (1 and 0 denote respectively the presence and the absence of the corresponding term), wi are the feature weights, and w0 is the bias. The SVM and LR classifiers perform very similarly when they are not under attack (i.e., for nmax ¼ 0), regardless of the fea-ture set size; therefore, according to the viewpoint of clas-sical performance evaluation, the designer could choose any of the eight models. However, security evaluation.

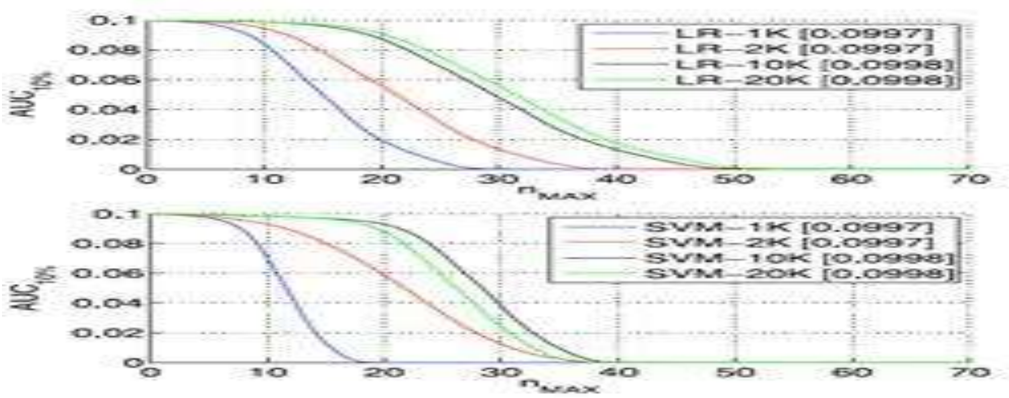

Fig. 2. AUC10 percent attained on TS as a function of nmax, for the LR (top) and SVM (bottom) classifier, with 1,000 (1K), 2,000 (2K), 10,000 (10K)

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and 20,000 (20K) features. The AUC10 percent value for nmax ¼ 0, corresponding to classical performance evaluation, is also reported in the legend between square brackets highlights that they exhibit a very different robustness to the considered attack, since their AUC10 percent value decreases at very different rates as nmax increases; in particular, the LR classifier with 20,000 features clearly outperforms all the other ones, for all nmax values. This result suggests the designer a very different choice than the one coming from classical performance evaluation: the LR classifier with 20,000 features should be selected, given that it exhibit the same accuracy as the other ones in the absence of attacks, and a higher security under the considered attack

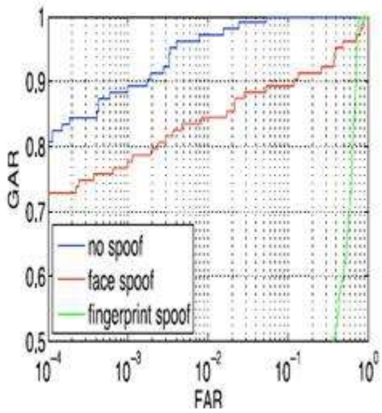

Fig. 3. ROC curves of the considered multimodal biometric system, under a simulated spoof attack against the fingerprint or the face matcher.

3.CONCLUSION

In this paper we focused on empirical security evaluation of pattern classifiers that have to be deployed in adversarial environments, and proposed how to revise the classical performance evaluation design step, which is not suitable forth is purpose. Our main contribution is a framework for empirical security evaluation that formalizes and generalizes ideas from previous work, and can be applied to different classifiers, learning algorithms, and classification tasks. It is grounded on a formal model of the adversary, and on a model of data distribution that can represent all the attacks considered in previous work; provides a systematic method for the generation of training and testing sets that enables security evaluation; and can accommodate application-specific techniques for attack simulation. An intrinsic limitation of our work is that security evaluation is carried out empirically, and it is thus data dependent; on the other hand, model-driven analyses [12], [10]require a full analytical model of the problem and of the adversary's behavior, that may be very difficult to develop for real-world applications. Another intrinsic limitation is due to fact that our method is not application-

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specific, and, therefore, provides only high-level guidelines for simulating attacks. Indeed, detailed guidelines require one to take into account application-specific constraints and adversary models.

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