StratDef: a strategic defense against adversarial attacks in malware detection

Aqib Rashid, Jose Such

Abstract—Over the years, most research towards defenses against adversarial attacks on machine learning models has been in the image recognition domain. The malware detection domain has received less attention despite its importance. Moreover, most work exploring these defenses has focused on several methods but with no strategy when applying them. In this paper, we introduce StratDef, which is a strategic defense system tailored for the malware detection domain based on a moving target defense approach. We overcome challenges related to the systematic construction, selection and strategic use of models to maximize adversarial robustness. StratDef dynamically and strategically chooses the best models to increase the uncertainty for the attacker whilst minimizing critical aspects in the adversarial ML domain like attack transferability. We provide the first comprehensive evaluation of defenses against adversarial attacks on machine learning for malware detection, where our threat model explores different levels of threat, attacker knowledge, capabilities, and attack intensities. We show that StratDef performs better than other defenses even when facing the peak adversarial threat. We also show that, of the existing defenses, only a few adversarially-trained models provide substantially better protection than just using vanilla models but are still outperformed by StratDef.

Key words—Adversarial machine learning, Malware detection, Machine learning security, Deep learning

1 INTRODUCTION

The advantages of ML models in fields such as image recognition, anomaly detection and malware detection are undisputed as they can offer unparalleled performance on large, complex datasets [1], [2]. Nevertheless, such models are vulnerable to adversarial examples [3], [4] which are inputs that are intentionally designed to induce a misclassification. Resilience against adversarial examples is essential and critical with much work having been carried out in the image recognition domain to defend against adversarial examples [5], [6], [7], [8], [9], [10]. However, these defenses are often less effective in the more constrained malware detection domain [11], [12]. Worryingly, out of the papers published in the last seven years on adversarial machine learning, approximately only 50 out of 3,000+ relate to the malware detection domain [13]. In fact, a recent survey that took an initial step towards evaluating defenses applied to this domain painted a bleak picture [14].

While complete security is difficult to achieve, a system’s goal should be to control the attack surface as much as possible to thwart attacks. Existing defenses in this regard are based on a variety of techniques [5] such as adversarial training [6], [15], gradient-based approaches [6], [16], feature-based approaches [7], [9] and randomization-based approaches [9], [10] with mixed success. Despite these multiple research efforts at developing defenses, there is little work approaching the problem from a strategic perspective. For this purpose, in other areas of cybersecurity, a moving target defense (MTD) is employed that continually varies itself to increase the uncertainty and complexity for the attacker, making reconnaissance and targeted attacks less successful [17], [18]. There are numerous ways that an MTD can vary itself, with some approaches having been applied to adversarial ML before [10], [19], [20], [21], but not in the malware detection domain nor in the depth we explore. Namely, we provide a method for constructing a strategic defense that embraces the key areas of model construction, model selection, and optimizer selection for a strategic MTD.

In this paper, we present our defense method, StratDef. We investigate how a strategic defense can offer better protection against adversarial attacks in the malware detection domain. We suggest methods to combat attacks strategically based on an MTD approach (rather than relying on a single model) by considering various factors that have not been explored in detail before, such as model heterogeneity, threat level, and information available about the attacker. Furthermore, we investigate various dimensions of a strategic MTD, such as what, how, and when it should adapt itself given the current environment it is operating within. Our goal is to make the job of the attacker more difficult by increasing the uncertainty and the complexity of the problem. Moreover, existing defenses do not consider a systematic model selection process for the ensemble [10], [19], [20], [21], [22], [23], [24]. This process is non-trivial and must deal with selecting the constituent models of the ensemble and then how to strategically use them. We demonstrate promising approaches for model selection and the subsequent, strategic use of the selected models for offering reliable predictions and protection against adversarial ML attacks. We further provide an experimental evaluation across Android and Windows to demonstrate the fragility of individual models and defenses compared with StratDef.

The main contributions of our work can be summarized as follows:

- We propose the first strategic defense against ad-
versarial attacks in the malware detection domain. Our defense, StratDef, is based on an MTD approach where we propose different strategic and heuristically-driven methods for determining what, how and when a defense system should move to achieve a high degree of adversarial robustness. This includes key steps related to model selection and the development of strategies.

- We offer a detailed evaluation of existing defensive approaches to demonstrate the necessity of a strategized approach by comparing existing defenses with ours. The results show that our strategized defense can increase accuracy by 50+4% in the most adverse conditions in both Android and Windows malware.
- We are the first to evaluate how a strategized defense based on MTD fares against a variety of attackers, such as gray-box attackers with limited knowledge, black-box attackers with zero-knowledge, and attackers who only use adversarial examples generated with Universal Adversarial Perturbations (UAPs).

The rest of this paper is organized as follows. Section 2 provides the background and puts StratDef in the context of related work. In Section 3 we define the threat model used in our work. In Section 4 we provide details about our defensive method, StratDef. In Sections 5 and 6 we present our experimental setting and results, respectively. We conclude in Section 7.

## 2 Background & related work

**Adversarial ML and Malware.** Machine learning is increasingly being relied on for the detection of malware. An ML-based malware detection classifier must be accurate and robust, as well as precise with good recall. The quality of such a classifier hinges on the features used during the training process. For software, the process of feature extraction is used to parse a software executable into its feature representation. Accordingly, the use of APIs, libraries, system calls, resources, or the accessing of network addresses, as well as the actual code are parsed into discrete, binary feature vectors to represent the presence or absence of a feature. Then, together with the class labels (i.e., benign and malware), models such as neural networks are trained on the feature vectors to classify unseen inputs.

However, the problem with using ML-based detection models is that they are vulnerable to adversarial examples [15]. These are inputs to ML models that are intentionally designed to fool a model by having the model output the attacker’s desired prediction through an evasion attack [29]. For example, an image of a panda may be incorrectly classified as a gibbon [30] or a truly malicious executable may be misclassified as benign [31]. In some cases, an adversarial example generated for a particular model may also evade another model too [15] due to transferability. To generate a new adversarial example for an image, an evasion attack can be performed by using one of several attacks from prior work, which perturb values in the feature vector representing the image (i.e., its pixels) [26], [30], [32], [33], [34], [35], [36], [37]. However, these attacks cannot be applied directly to the malware detection domain as they make arbitrary perturbations to continuous feature vectors. When building an adversarial example for the malware detection domain, the malicious functionality must be preserved (in the feature-space) and the feature vector must remain discrete [12], [38], [39], [40], [41], [12], [43]. For example, a feature representing an API call (e.g., GetTempPath()) cannot be perturbed continuously (e.g., GetTempPath() + 0.001). Instead, an entirely new feature must be used [12], [38]. This increases the complexity of working in this domain. To deal with this, when perturbations are applied by an attack, it must be ensured that they are permitted and proper to cater to the constraints imposed by this domain. For this, we present a method to achieve a lower bound of functionality-preservation in the feature-space (see Section 5 later).

**Defenses.** To deal with this threat, several defenses have been proposed, mainly for the image recognition domain, with mixed success [14], [44]. These include a range of techniques such as adversarial training [6], [15], gradient-based approaches [6], [16], feature-based approaches [7], [8] and randomization-based approaches [9]. For example, Papernot et al. proposed defensive distillation [16] which involves utilizing different-sized neural networks to improve the generalization of the main model, though Stokes et al. [45] found this to be ineffective when applied to the malware detection domain. Wang et al. proposed random feature nullification, which decreases the attacker’s chances of using features that are important to the model [9]. This is only effective if the attacker chooses to perturb features randomly as well [14]. Xie et al. [9] also proposed a randomization-based defense, though this has been shown to be ineffective by Athayle et al. [46]. Another approach is to mask and obfuscate gradients, though this has been found ineffective in later work [47]. Podschwadt et al. found that adversarial training (first proposed in [15]) is a potentially effective defense method [14] though it cannot protect against unknown and unseen threats. Moreover, in our work we identify and validate some issues with this method. For example, adversarial training introduces additional complexities such as determining which model to choose as the base model, what to train on, and how much to train. However, as we show, StratDef assists with this, as it helps to select the most promising models and then choose between them strategically at prediction-time. This produces better results than a single model trained adversarially as shown in Section 6.

**Moving target defenses.** In a moving target defense (MTD), the configuration of the defense changes regularly. The key design principles of an MTD include the “what to move”, the “how to move” and the “when to move” [18]. In the context of adversarial ML, this typically involves moving between the ML models used to make predictions. Thus, MTDs can be considered to belong to the family of ensemble defenses. The objective is to make it more challenging for attackers to perform meaningful reconnaissance and successful attacks [18], which will be rendered difficult as the target model will not be static. Different MTD approaches have offered some success in other domains [10], [19], [20], [21], but have never been applied to the malware detection domain before. To the best of our knowledge, we are the first to explore how an MTD approach can defend against adversarial attacks in the ML-based malware detection domain with our defense, StratDef. StratDef advances the state
of the art by embracing the key principles of an MTD. Rather than plainly utilizing an MTD approach with a group of models, StratDef provides an entire framework for generating models, selecting those models systematically, and producing reliable strategies to use those models to offer accurate predictions against legitimate inputs whilst defending against adversarial examples.

Existing MTD approaches from other domains do not consider various key factors that we explore, such as the challenges related to the systematic construction, selection, and strategic use of models to maximize adversarial robustness. For example, prior MTD-based work only uses small ensembles of models, consisting mainly of DNNs as the constituent models, and varies these DNNs only in their training procedure. We explore how and to what degree the model selection procedure should be heuristically-driven to promote key aspects such as heterogeneity, redundancy, and to minimize the effect of transferability of adversarial examples across models. Moreover, unlike other defenses, StratDef can give consideration to information available about its operating environment to provide an adapted and tailored response based on the current threat level when information is available.

Next, we introduce the threat model used in our work, followed by a detailed description of our defense, StratDef.

3 Threat Model

Feature-based ML malware detection is a domain that has been widely explored in previous work [25], [51], [52], [48], [49], [50]. Our work focuses on the same well-established threat model concerning the evasion of such malware detection classifiers.

Application model. To construct a classifier for malware detection, executables are represented as binary feature vectors. Datasets provide a comprehensive set of extracted features from real-world executables. With these datasets and features 1...Φ, we can construct a vector X for each input sample such that X ∈ {0, 1}^Φ. X_i = 1 indicates the presence of feature i and X_i = 0 indicates its absence. We use the feature vectors and associated class labels to construct binary classification models for malware detection as shown in Figure [1]

fig: Overview of a malware detection classifier: the dataset provides features that are processed into feature vectors of size Φ. Class labels are assigned to each input sample. Feature vectors and class labels form training data.

Attacker’s goal. The attacker’s goal is to generate adversarial examples to evade a malware detection classifier. Suppose we have a classifier F, where F: X ∈ {0, 1}^Φ and a function chk(·) to check the functionality of an input sample. Then, this goal can be summarized as:

\[ \text{chk}(X) = \text{chk}(X'); F(X) = 1; F(X') = 0 \] (1)

We use 0 to represent the benign class and 1 for the malware class. The attacker wants to generate an adversarial example X’ that is functionally-equivalent to the original malware sample X, but is predicted as benign by F.

Attacker knowledge & capability. For the majority of the paper, we model all attackers who interact with StratDef in a gray-box setting with limited knowledge about the target model, like previous work [29], [51], [52], [53]. In our threat model, attackers have access to the same training data as the target model and have knowledge of the feature representation. However, attackers have no knowledge of the parameters, configurations, or constituent models of StratDef nor of other evaluated defenses. Therefore, they must train substitute models using the training data and attack them, hoping that the generated adversarial examples will transfer to the target model [15], [47], [51]. This is based on the well-established idea that adversarial examples for other different models can be used to evade the target model [15].

Furthermore, we use different scenarios involving attacker capabilities and attack intensities with the goal of studying and evaluating the performance of StratDef under different threat levels like prior work [12], [44], [48], [53], [54], [55]. Attackers may differ in their behavior, the strength and intensity of their attacks, their ability to generate adversarial examples, and more. For deployment, in the absence of any information about the operating environment, StratDef assumes the highest threat level, consisting of the most adverse environment, with the strongest attacker. However, if there is information about the environment and/or the attackers within (e.g., through cyber-threat intelligence [56], [57]), StratDef can use it to provide a more targeted defensive approach. Therefore, in our evaluation (see Section 6), we show how StratDef performs against different attacker scenarios and intensities to show the whole range of its capabilities. Nonetheless, for the comparison with other defenses, we focus on the strongest attacker as this is the default scenario when no information is available about the attacker or environment.

Finally, we evaluate StratDef’s performance against a black-box attacker with zero knowledge as featured in previous work [27], [29], [41], [47], [58], [59], [60], [61], [62], [63]. This attacker only has access to the predictions of StratDef, with no other knowledge. The attacker constructs a substitute model by querying the target model systematically. The substitute model is attacked, in the hope that any generated adversarial examples transfer to the target model [15].

4 StratDef

In this section, we firstly describe our strategic method, StratDef, at a high-level and then provide details about each of its steps. StratDef embraces the three key design principles of an MTD: what to move, how to move and when to move [17], [18], [22]. We present an overview of StratDef in Figure [2]. In our method, we provide a systematic and heuristic model selection approach to determine what to move considering the current user type, the threat level, and
performance metrics. With this method, StratDef’s behavior can be optimized according to the situation; for example, if a particular metric needs to be prioritized, the model selection can be adjusted accordingly (as we describe later). Once models have been selected, we can strategize how they will be used. In cybersecurity, an MTD typically cycles through configurations during its deployment. Since StratDef makes predictions for legitimate and adversarial inputs, we use a strategy to choose a model at prediction-time, thereby strategically cycling through the models when it is time to move. We explore multiple methods to determine this strategy, ranging from uniform random probability, a game-theoretic approach based on Bayesian Stackelberg Games and a strategic heuristically-driven approach.

4.2 What to move: Phase 2 - Model selection
Continuing offline, model selection is performed to produce a strong, heterogeneous ensemble of models. To the best of our knowledge, we are the first to offer a flexible method to select models systematically by considering model performance and threat levels. Recalling from the threat model, StratDef provides a tailored defense by considering the information it may have about its operating environment. If no specific information is available, the highest threat level is assumed (i.e., the strongest attacker and highest attack intensity). To achieve this, we simulate threat levels by generating adversarial examples using a set of substitute models (see Sections 5.2 & 5.4 later).

Each candidate model \( F \in U \) is then evaluated under each threat level using several machine learning metrics. This allows us to aggregate the metrics into a \textit{consideration score} for each candidate model at each threat level, thereby encapsulating the performance of a model across threat levels. A higher consideration score indicates better performance of a model, which increases its chances of inclusion in the ensemble. The actual formula for the consideration score varies based on the deployment needs and requirements (e.g., one may be more interested in minimizing false positives over other metrics — see Section 5.3 later for the specific formula we use).

Hence, in Equation 2, we provide a general formula for the consideration score:

\[
S_{F,\gamma,\alpha} = \oplus(m_{F,\gamma,\alpha}^1, m_{F,\gamma,\alpha}^2, \ldots, m_{F,\gamma,\alpha}^n)
\]  

\(S_{F,\gamma,\alpha}\) refers to the consideration score of a candidate model \( F \in U \) at attack intensity \( \alpha \) against attacker \( \gamma \). A particular combination of each metric chosen by the defender is considered (e.g., whether metrics are weighted, maximized, minimized, etc.). For the \( n \) considered metrics, \( m_{F,\gamma,\alpha} \) refers to the metric \( m \) for the candidate model \( F \) at attack intensity \( \alpha \) against attacker \( \gamma \). Depending on the situation, one may adjust the considered metrics or use different metrics altogether to produce a new model selection.

Once consideration scores are produced, the candidate models are sorted in descending order by their consideration scores at each threat level (i.e., each attack intensity \( \alpha \) and each attacker \( \gamma \)). Essentially, these models have been sorted by their performance considering several ML metrics at different threat levels. This drives the model selection method. We explore two different model selection methods (and evaluate them later in Section 6):

- **Best**: This method selects the best-performing models with the aim to maximize performance across the considered metrics. For each attacker and attack intensity, we select the \( k \) highest-scoring models out of all potential candidates in \( U \). \( k \) is a hyperparameter and can be chosen by the defender according to their requirements and resources (e.g., a more resourceful defender may want to use more models).
- **Variety**: This method aims to reduce transferability among the selected models by enforcing diversity.
in the model selection. The highest-scoring model from each model family in $U$ is selected at each attack intensity against each attacker. The number of models selected per $\alpha$ is equal to the number of model families.

The model selections for each attack intensity $\alpha$ for each attacker $\gamma$ are pooled together and represented by $\Sigma_\gamma$. If no information is available about the environment, $\gamma$ represents a strong attacker, with the most capable models selected to deal with this. This model selection procedure offers a systematic yet flexible approach to the defender, allowing them to adjust the considered metrics, which would adapt StratDef to their needs.

4.3 How to move: Devising a strategy

An optimizer is then used to strategize how each model selected in the previous step will be chosen at prediction-time by StratDef. This step takes place offline and corresponds to choosing an optimizer in Figure 2. Each optimizer produces a global strategy vector $Z_\gamma$ for an attacker $\gamma$ using data about the models (more detail below). The probability of StratDef choosing each model from $\Sigma_\gamma$ at attack intensity $\alpha$ against attacker $\gamma$ is contained within $Z_{\gamma,\alpha}$. This means that the strategy chooses from the most suitable models to make the prediction by adapting to the attack intensity and the attacker type. For devising strategies, we explore three optimizers (and evaluate them later in Section 5).

Game-theoretic optimizer (GT). We can model the problem of adversarial examples as a min-max game between an attacker and a defender, following the well-established concept of Security Games. This has been successfully applied to various areas of both physical security and cybersecurity [64]. Specifically, the attacker is trying to maximize the loss of the classifier, while the defender is trying to minimize it.

Hence, we model the interaction between the defender ($D$) and the user — who can be either a legitimate user ($L$) or an attacker ($\gamma$) — as a Bayesian Stackelberg Game [65]. The defender is the leader, and the user is the follower. The defender aims to maximize its expected reward over its switching strategy and the strategy vector played by the followers. We produce payoff matrices for each game between the defender and each user. The game between the defender and the attacker is modelled as a constant-sum game like previous work in other domains [10], [19]. There, the utilities are based on the evasion rates of each attack (the attacker’s possible move) against each model (the defender’s possible move). However, this is inadequate in the malware detection domain because of the disparity between the number of adversarial examples and their evasion rate. A stronger attacker can generate a greater number of more evasive adversarial examples than a weaker one. Therefore, we use a normalized evasion rate to encapsulate information about the scale and evasion rate.

We provide details of the procedure below. Let $\Omega_{\tau,S}$ represent the set of adversarial examples generated by an attack $\tau$ for some substitute model $S$ which is used to generate adversarial examples (see Sections 5.2 & 5.4 later):

1) Evaluate each set of adversarial examples $\Omega_{\tau,S}$ against each selected model $F \in \Sigma_\gamma$ to obtain the evasion rate.

2) Compute the normalized evasion rate ($R_{\tau,S,F}$) to reflect the evasive capability of the set $\Omega_{\tau,S}$ against model $F$. For this, multiply the number of adversarial examples in each set by the evasion rate and normalize between 0 and 100, which is the frequent setup for the game between attacker and defender as a constant-sum game (= 100) [10], [19].

3) Produce payoff matrices, where the defender is the row player, for each game by calculating rewards:

   a) For the constant-sum game between $D$ and $\gamma$, the attacker’s reward is equal to the normalized evasion rate $R_{\tau,S,F}$. The defender’s reward, because it is a constant-sum game, is therefore equal to $100 - R_{\tau,S,F}$.

   b) For the game between $D$ and $L$, the reward for both players is equal to the accuracy of the model $F$ (i.e., the defender’s possible move).

4) Feed both payoff matrices into a Bayesian Stackelberg solver (such as [64], [66]) along with the attack intensities. This produces a strategy vector $Z_{\gamma,\alpha}$ containing the probability of playing each model $F \in \Sigma_\gamma$ against attacker $\gamma$ at attack intensity $\alpha$.

In the optimization problem, $\alpha$ is a hyperparameter modelled as a trade-off between accuracy on legitimate and adversarial inputs corresponding to the attack intensity. The optimization problem may result in a pure strategy (where only a single model is chosen for predictions) or a mixed strategy (where there is a choice between multiple models). A pure strategy can be produced when one of the models is more robust to attacks than others. At $\alpha = 0$, StratDef is only concerned with accuracy on legitimate inputs, and therefore a pure strategy of the most accurate model is produced.

Strategic ranked optimizer (Ranked). We use the consideration scores for each model in the set $\Sigma_{\gamma,\alpha}$ (the models selected for attacker $\gamma$ at attack intensity $\alpha$) to produce a strategy vector. At $\alpha = 0$, a pure strategy consisting of the most accurate model is produced. For $\alpha > 0$, each model in the set is sorted by its consideration score. A rank is then assigned to each model in the sorted set with the lowest-scoring model having a rank of 1, with this increasing as the model scores increase. Based on this, each model is assigned a probability in $Z_{\gamma,\alpha}$ as per Equation 3

$$p(F, \gamma, \alpha) = \frac{r_{F,\gamma,\alpha}}{\sum_{G \in \Sigma_{\gamma,\alpha}} r_{G,\gamma,\alpha}}$$

$r_{F,\gamma,\alpha}$ is the rank of model $F$ at attack intensity $\alpha$ against attacker $\gamma$. In other words, the probability of a model $F$ being selected is its rank divided by the sum of all ranks. Therefore, we assign the highest probability to the highest-scoring model. In $Z_{\gamma,\alpha}$, a probability of 0 is assigned to models that are not in $\Sigma_{\gamma,\alpha}$. In other words, if a model was not selected at a particular attack intensity, it will have a probability of 0 in the strategy vector. This approach will always generate a mixed strategy at every attack intensity except $\alpha = 0$.

Uniform random strategy (URS). This approach assigns a uniform probability to each model in $\Sigma_\gamma$ and only acts as a baseline for comparing with the other approaches, as it...
is not expected to give the best performance. It maximizes the uncertainty for the attacker with regard to the model that is selected at prediction-time. Thus, the probability is calculated according to Equation 4:

\[ p(F, \gamma, \alpha) = \frac{1}{|\Sigma|} \]  

(4)

In Appendix B, we provide example strategy vectors with the values in the vectors corresponding to the probability of choosing model \( F \in \Sigma_\gamma \) at attack intensity \( \alpha \).

### 4.4 When to move: Making a prediction

After the offline generation and selection of the best models, and the creation of the strategies to move between the selected models — that is, the strategy vector \( Z_\gamma \) to move between models in the set \( \Sigma_\gamma \) — StratDef is now ready to be deployed online and start making predictions. As per Figure 2, when a user requests a prediction, StratDef will choose a model to pass the input to by rolling a biased die using the probabilities in the strategy vector \( Z_{\gamma, \alpha} \) in real-time and choose a model from \( \Sigma_\gamma \), which will actually make the prediction. As always, in the absence of information about the threat level of the environment, StratDef will assume it is facing the strong attacker at the highest attack intensity. Because the actual model that is used by StratDef to make each prediction will be chosen dynamically, the user will have it difficult to know which model was used each time. Therefore, our hypothesis is that if the previous steps are performed systematically following our method, StratDef will offer sound and robust predictions, whilst revealing minimal information about itself.

Next, we show how StratDef performs better than existing defenses in the malware detection domain in the face of adversarial examples. In the following section, we provide details of the experimental setup we consider for the evaluation, together with details about how we generate adversarial examples.

### 5 Experimental Setup

#### 5.1 Datasets

We perform our evaluation with two well-known datasets. The Android DREBIN dataset [67] consists of 123453 benign samples and 5560 malware samples. There is a total of eight feature families consisting of extracted static features ranging from permissions, API calls, hardware requests and URL requests. To keep our dataset balanced, we use 5560 samples from each class (benign and malware), resulting in a total of 11120 samples with 58975 unique features. The Windows SLEIPNIR dataset [26] consists of 19696 benign samples and 34994 malware samples. The features of this dataset are derived from API calls in PE files parsed into a vector representation by the LIEF library [26, 68]. We use 19696 samples from each class, resulting in a total of 39392 samples with 22761 unique features. Both datasets are transformed into a binary feature-space with each input sample transformed into a feature vector representation. The datasets are initially split using an 80:20 ratio for training and test data using the Pareto principle. After this, the training data is further split using an 80:20 ratio to produce training data and validation data. This effectively produces a 64:16:20 split, which is a technique that has been widely used before [69, 70, 71, 72, 73, 74].

#### 5.2 Generating adversarial examples

We generate adversarial examples in the feature-space like previous work [26, 28, 31, 75]. When doing this, we ensure that feature vectors remain discrete and that malicious functionality is preserved by limiting the set of allowed perturbations that can be applied to the feature vector. This ensures that adversarial examples remain close to realistic and functional malware, without the need for testing in a sandbox environment.

**Preliminaries.** There are two types of perturbations that can be applied to a feature vector. Feature addition is where a value in a feature vector is modified from 0 to 1. In the problem-space, an attacker can achieve this in different ways, such as adding dead code so that the feature vector representing the software changes to perform this perturbation. This has proved to work well to create adversarial malware, for instance in Windows [62]. It should be noted that analysis of the call graph by a defender may be able to detect the dead code. Meanwhile, feature removal is where a value in a feature vector is modified from 1 to 0. This is a more complex operation, as there is a chance of removing features affecting functionality [12, 75, 76, 77]. For Android apps, an attacker cannot remove features from the manifest file nor intent filter, and component names must be consistently named. Furthermore, the S6 feature family of DREBIN is dependent upon other feature families and cannot be removed. Therefore, the opportunities for feature removal lie in areas such as rewriting dexcode to achieve the same functionality, encrypting system/API calls and network addresses. For example, obfuscating API calls would allow those features to be removed (since they would then count as new features) even though the functionality would remain [12, 75].

For each dataset, we determine the allowed perturbations by consulting with industry documentation and previous work [12, 25, 73, 75, 76, 77, 78]. DREBIN allows for both feature addition and removal, with Table 1 providing a summary of the allowed perturbations for each of the feature families [76, 77]. For SLEIPNIR, we can only perform feature addition because of the encapsulation performed by the feature extraction mechanism of LIEF when the dataset was originally developed.

| Feature set | Addition | Removal |
|-------------|----------|---------|
| S1 Hardware | ✓        |         |
| S2 Requested permissions | ✓        |         |
| S3 Application components | ✓        |         |
| S4 Intents | ✓        |         |
| S5 Suspicious API calls | ✓        |         |
| S6 Network addresses | ✓        |         |

**TABLE 1:** Allowed perturbations for DREBIN feature families.

We include a verification step in our attack pipeline to monitor perturbations applied to a feature vector. Firstly, attacks are applied to malware samples to generate adversarial examples without any limitations. Then, because the attacks we use produce continuous feature vectors, their
values are rounded to the nearest integer (i.e., 0 or 1) to represent the presence or absence of that feature. Each adversarial example is then inspected for prohibited perturbations, which are reversed. As this process can change back features used to cross the decision boundary, we then ensure that the adversarial example is still adversarial by testing it on the model.

**Procedure.** As detailed in Section 3 our threat model mainly consists of a gray-box scenario where the attacker’s knowledge is limited [29], [51], [52], [53], so we focus in this section on describing the process we follow for this. We also consider a black-box scenario, but this is described in detail in Section 6.5. In particular, for the gray-box scenario, attackers have access to the same training data as the target model and have knowledge of the feature representation. Therefore, to simulate this scenario, we construct four substitute vanilla models using the training data: a decision tree (DT), neural network (NN), random forest (RF) and support vector machine (SVM) (see Appendix A for model architectures). It is well established that using models with architectures different to the target model can be used to evade it [15]. Therefore, we apply the attacks listed in Table 2 against these substitute models to generate adversarial examples. We can apply white-box attacks to the substitute models because we have access to their gradient information. An overview of the procedure for generating adversarial examples is provided:

1) With an input malware sample and an (applicable) substitute model (S), an attack (τ) is performed, to generate an adversarial example. The malware samples are those from our test set.

2) If the generated feature vector is continuous, the values within are rounded to the nearest integer (i.e., 0 or 1), in order to restore it to a discrete vector.

3) We then verify that all perturbations are valid according to the dataset. Any invalid perturbations are reverted, to offer a lower bound of functionality preservation within the feature-space.

4) The adversarial example is then evaluated to ensure it is still adversarial. The substitute model S makes a prediction for the original input sample and the adversarial example; a difference between them indicates that the adversarial example has crossed the decision boundary. If so, it is added to the set of adversarial examples generated by attack τ against S, which is represented by $\Omega_{\tau,S}$.

5) The sets of adversarial examples can be tested on StratDef, following the steps in the next sections.

This process results in 4608 unique adversarial examples for DREBIN and 5640 for SLEIPNIR. $\Omega_{DREBIN}$ and $\Omega_{SLEIPNIR}$ are the sets of adversarial examples for DREBIN and SLEIPNIR respectively. The procedure is performed by the defender and the attacker independently. Different attacker profiles are then constructed as described in Section 5.4 based on the generated adversarial examples. The defender uses the generated adversarial examples (together with the training and validation data) as part of the process described in the next sections.

### Table 2: Attacks used to generate adversarial examples.

| Attack name                              | Applicable model families |
|-----------------------------------------|---------------------------|
| Basic Iterative Method (A) [33]          | NN                        |
| Basic Iterative Method (B) [33]          | NN                        |
| Boundary Attack [54]                    | DT, NN, RF, SVM           |
| Carlini Attack [42]                      | NN, SVM                   |
| Decision Tree Attack [57]               | DT                        |
| Deepfool Attack [39]                    | NN, SVM                   |
| Fast Gradient Sign Method [53] [55]      | NN, SVM                   |
| Hough Attack [53]                       | DT, NN, RF, SVM           |
| Jacobian Saliency Map Approach [37]      | NN, SVM                   |
| Project Gradient Divergence [50]         | NN, SVM                   |
| Support Vector Machine Attack [40]       | SVM                       |

#### 5.3 Training models & defenses

**Other models & defenses.** To construct all models, we use the scikit-learn [81], Keras [82] and Tensorflow [83] libraries. We construct four vanilla models (see Appendix A for architectures). Vanilla models are the base models for defenses such as ensemble adversarial training [6], [15], defensive distillation [16], SecSVM [28], and random feature nullification [25]. For adversarial training, we train the vanilla models with different sized batches of adversarial examples (ranging from 0.1% to 25%) from those generated previously. For example, suppose the size of the test set is 2224 (which is equally split between benign and malware samples); then for a 0.05 model variant (e.g., NN-AT-0.05), we select 56 adversarial examples (i.e., 5% of half the test set size) and add these to the training set. We then train the vanilla and SecSVM models to produce adversarially-trained models. We found in preliminary work that adversarially training beyond 25% increases time and storage costs as well as overfitting. We apply defensive distillation to the vanilla NN model, whilst random feature nullification is applied to all vanilla models. The vanilla SVM model acts as the base model for SecSVM. We also compare StratDef with the voting defense. Voting has been applied to other domains [22] and to the malware detection domain [23], [24].

This is similar to a Multi-Variant Execution Environment (MVEE) where an input sample is fed into multiple models in order to assess divergence and majority voting is used for the prediction [84], [85]. We use the same constituent models for the voting defense as for StratDef (and thus the naming conventions are similar). We consider two voting approaches that have been tested in prior work [23], [24]: majority voting and veto voting. The better of the two approaches is compared with StratDef. In preliminary work, we discover that veto voting causes higher false positive rate (FPR) in both datasets — as high as 25% in DREBIN (see Appendix C). This poor performance may be because the voting system is forced to accept any false positive prediction from its constituent models. Therefore, we focus on comparing StratDef with majority voting using the same model selections.

**StratDef.** To construct different StratDef configurations, we follow the offline steps described in Section 4 to construct models and devise strategies. The candidate models are the individual models and defenses trained as described above (except voting). We aim to maximize the accuracy and robustness on input samples whilst minimizing false predictions. To achieve this, we use the formula in Equation 5 for the consideration scores, where we maximize accuracy (ACC), AUC, F1 and minimize FPR and false negative rate.
$S_{F,\gamma,\alpha} = ACC_{F,\gamma,\alpha} + F1_{F,\gamma,\alpha} + AUC_{F,\gamma,\alpha} - FPR_{F,\gamma,\alpha} - FNR_{F,\gamma,\alpha}$

Equation (5)

$S_{F,\gamma,\alpha}$ is the consideration score of the candidate model $F$ at attack intensity $\alpha$ against attacker $\gamma$. The value of each metric for the candidate model $F$ at attack intensity $\alpha$ against attacker $\gamma$ is represented accordingly. We use all combinations of the Best (with $k = 5$) and Variety model selection methods with the three optimizers described in Section 4.3 to produce six StratDef configurations (see Appendix B for example strategies developed by StratDef).

5.4 Modelling gray-box attacker profiles

After generating each set of adversarial examples $\Omega_{\tau,S}$ as detailed in Section 5.2, we assign each set to different attacker profiles, according to Table 3. The aim is to simulate and evaluate StratDef’s performance against different types of attackers in accordance with previous work [12], [48], [51], [52], [53]. Modelling attacker profiles, we ensure that the strongest attacker only uses the sets of adversarial examples with higher normalized evasion rates (see Section 4.3) against each model $F \in \Sigma_{\gamma}$. Weaker attackers use those with lower normalized evasion rates. Additionally, stronger attackers can observe transferability. If an attacker cannot observe transferability, then when assigning them a set, we only consider the normalized evasion rate against the substitute model $S$, which is the original applicable substitute model, and not against models in $\Sigma_{\gamma}$, which could be higher due to transferability.

Once an attacker has been assigned sets of adversarial examples, the sets are aggregated into a single set; each attacker now has a selection of adversarial examples to model and represent their capability. Using these, we create datasets to represent different attack intensities, represented by $\alpha$, for each attacker. The intensity represents the proportion of adversarial examples in the dataset (i.e., adversarial queries made by attackers). Each of these datasets corresponds to a value of $\alpha \in [0, 1]$ with increments of 0.1. For example, at $\alpha = 0.1$, 10% of the dataset consists of adversarial examples. The remaining 90% consists of an equal number of benign and non-adversarial malware samples from the test set described in Section 5.1. The pooling procedure in Table 3 governs how the adversarial examples for the $\alpha$ datasets are chosen. For the strong attacker, the construction of these datasets gives preference to more evasive adversarial examples from their aggregated set. For other attackers, the adversarial examples are chosen randomly from their aggregated set. Finally, the universal attacker only gets assigned adversarial examples with universal adversarial perturbations (UAPs) [7], [86]. In total, there are 1541 such universal examples for DREBIN ($UAP_{DREBIN}$) and 2217 for SLEIPNIR ($UAP_{SLEIPNIR}$).

The datasets generated for each attacker are also used by the defender for developing strategies (as per Section 4.2) and for evaluating the performance of each defense by simulating attackers with different levels of adversarial queries.

| Attacker | Strength | Observe transferability | Pooling procedure |
|----------|----------|-------------------------|-------------------|
| Peak     | $R_{\varepsilon\neq F}$ | Yes | Random |
| Medium   | $0 \leq R_{\varepsilon\neq F} \leq 50$ | Yes | Weighted based on $R_{\varepsilon\neq F}$ |
| Strong   | $50 \leq R_{\varepsilon\neq F}$ | Yes | Random |
| Random   | Any      | Yes | Random |
| Universal| UAPs only| Yes | Random |

Table 3: Profiles of different gray-box attackers who interact with StratDef. For the black-box attacker, see Section 6.5.

6 Evaluation

In this section, we present an evaluation across Android and Windows in the experimental setting described previously. In Section 6.1, we demonstrate the performance of StratDef under different threat levels. We compare StratDef to other defenses in Sections 6.2 and 6.3. Then, we show how StratDef performs against Universal Adversarial Perturbations (Section 6.4). Finally, we show how StratDef copes with a complete black-box attacker (Section 6.5).

6.1 Performance of StratDef

We present the results for the StratDef configurations against different attackers and attack intensities. Figure 3 shows that as the threat level increases (stronger attackers and higher intensities), there is a greater effect on the performance of StratDef. At the peak threat level, StratDef achieves 52.4% accuracy for DREBIN and 100% accuracy for SLEIPNIR (with the highest average accuracy of 72.7% for DREBIN and 96.2% for SLEIPNIR across all configurations). $\Omega_{DREBIN}$ is more evasive than $\Omega_{SLEIPNIR}$ as indicated by StratDef’s lower accuracy. Despite the greater size of $\Omega_{SLEIPNIR}$, StratDef only drops to 71% accuracy. The weaker adversarial examples for SLEIPNIR can be attributed to more limitations in the perturbations that can be applied, therefore reducing the attack surface.

In terms of model selection, the Variety model selection performs well at all threat levels. This is due to greater model diversity that offsets the transferability of attacks. Regarding the optimizer, the game-theoretic configurations offer the best accuracy for both datasets. However, these configurations switch between pure and mixed strategies, with adversarially-trained models featuring more often in the strategies. In fact, only up to 30% of the model selection is used against the strong attacker, meaning that the majority of the model selection is never used. Contrarily, the strategic ranked optimizer only produces mixed strategies since it does not give complete preference to the strongest model. Despite using more models, it offers similar performance to the GT optimizer, as visible in Figure 4.
StratDef also outperforms voting. At the peak adversarial threat, the Voting-Best-Majority and Voting-Variety-Majority configurations are on par with vanilla models and existing defenses against $\Omega_{DREBIN}$, only achieving a maximum of 30% accuracy but with high false readings. Against $\Omega_{SLEIPNIR}$ the voting defense can achieve 90+% accuracy, with adequate F1 and AUC metrics. However, as it can be seen in Appendix B this comes at the cost of higher FPR and FNR than the StratDef Best and Variety configurations.

Using fewer models may increase the risk of an attacker discovering the profile and configuration of the deployed defense. However, due to transferability, more models may be an avenue for greater evasion. Therefore, a trade-off exists between the number of models used and the robustness of the system. If a more diverse set of models is used to reduce the transferability, the attacker will be less successful. Meanwhile, the expected poor performance of the uniform random strategy (URS) approach highlights the need for good strategies, regardless of how strong the model selection is. Using a randomized strategy is no competitor to a game-theoretic or heuristically-driven strategy.

### 6.2 StratDef vs. other defenses

The models and defenses we evaluate (bar high levels of adversarial training, further discussed later) perform significantly worse than StratDef, especially at the highest threat level. We present some in Figure 3 — for full results, see Appendix D. The NN and SVM models only achieve 7% and 2% accuracy, with this peaking at only 18% and 22% for defensive distillation (NN-DD) and SecSVM respectively. Interestingly, in some instances, the vanilla random forest (RF) for DREBIN and the decision tree (DT) for SLEIPNIR can surpass defenses such as random feature nullification (RFN), though at the cost of higher FPR. For both datasets, the DT-RFN model can achieve equal or higher robustness than the best-performing adversarially-trained models. StratDef also outperforms voting. At the peak adversarial threat, the Voting-Best-Majority and Voting-Variety-Majority configurations are on par with vanilla models and existing defenses against $\Omega_{DREBIN}$, only achieving a maximum of 30% accuracy but with high false readings. Against $\Omega_{SLEIPNIR}$ the voting defense can achieve 90+% accuracy, with adequate F1 and AUC metrics. However, as it can be seen in Appendix B this comes at the cost of higher FPR and FNR than the StratDef Best and Variety configurations.

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tionally, StratDef has a benefit over single adversarially-trained models as it complicates the attacker’s efforts to construct substitute models, reducing the success of black-box attacks (as seen later).

### 6.3 Efficiency of StratDef

We also assess the efficiency of StratDef, voting, and some other best-performing defenses. Figure 6 shows the average time taken by each defense to produce a single prediction against the strong attacker. There is a significant time difference between StratDef and voting, as voting uses more models for a single prediction. StratDef returns predictions in a similar time to single-model defenses, as only a single model is used for a prediction with a minimal overhead involved in rolling a biased die to choose the model. In fact, StratDef returns faster predictions on average than RF-AT-0.25 for DREBIN. Prior work has found that random forests are generally slower than other models for predictions [87], [88], and it seems against StratDef too.

Figure 6: Average time taken per prediction against the strong attacker.

![Fig. 6: Average time taken per prediction against the strong attacker.](image)

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Figure 7 shows the average memory consumption of each defense across attack intensities. Other defenses have static memory consumption as they are not strategized for the attack intensity. The single-model defenses evaluate consume less memory, with minor differences due to the particular model family. Meanwhile, ensemble defenses require access to more models at prediction-time leading to higher memory costs. Voting has the highest memory consumption since it uses all models in the ensemble for a single prediction — in the case of Voting-Variety-Majority for SLEIPNIR, a single, memory-intensive model requires 700+ MB. Meanwhile, StratDef is efficient — and better than voting — as it only loads models for each attack intensity with a non-zero probability (i.e., those that have a chance of being chosen to make a prediction). Overall, StratDef — which is an ensemble defense — performs as efficiently as (and sometimes better than) single-model defenses considering both time and memory costs.

Figure 7: Average memory consumption of models against the strong attacker.

![Fig. 7: Average memory consumption of models against the strong attacker.](image)

### 6.4 StratDef vs. UAPs

Recent work has uncovered universal adversarial perturbations (UAPs) as a cost-effective method of generating adversarial examples [78], [86]. We evaluate how StratDef performs against the universal attacker who only uses adversarial examples generated from UAPs. In total, there are 1541 such adversarial examples for DREBIN ($UAP_{DREBIN}$) and 2217 for SLEIPNIR ($UAP_{SLEIPNIR}$) available.

![Fig. 8: Accuracy of different defenses against universal attacker.](image)

Figure 8 shows the accuracy of StratDef configurations and other best-performing models against the universal attacker — see Appendix [D] for extended results.

### 6.5 StratDef vs. black-box attacks

We also explore how StratDef performs against a complete black-box attack. In this setting, a zero-knowledge attacker queries StratDef as an oracle to develop a substitute model that they can attack [47].
Procedure. We compare StratDef with other well-performing defenses in this attack. For this, we follow the standard procedure to conduct and evaluate black-box attacks \textsuperscript{[27, 47, 58, 60]}. To begin the attack against the target model, we query the model with an equal number of benign and malware samples\textsuperscript{2}. We vary the number of samples at training-time to examine if this affects the success of attacks, as more interactions at training-time should produce a better representation of the target model. The input-output relations from querying the target model are used to train a substitute DNN — see Appendix A for model parameters of the neural network. This is based on the well-established idea that attacks against a substitute model may transfer to the target oracle \textsuperscript{[15]}. Therefore, against the substitute model, we use white-box attacks such as BIM \textsuperscript{[33]}, FGSM \textsuperscript{[30, 50]}, JSMA \textsuperscript{[37]} and PGD \textsuperscript{[56]} to generate adversarial examples that are tested against the target models such as StratDef and other defenses. StratDef assumes the highest threat level, (i.e., the strongest attacker at the highest attack intensity). Beyond this, StratDef is not strategized to deal with a black-box attack. Therefore, this attack also helps us see how StratDef may work against an unknown attacker. We also evaluate other target models.

Results. As in previous work that evaluated black-box attacks \textsuperscript{[47, 60]}, we evaluate the success rate against each model (i.e., the number of adversarial examples that evade the target model over the number of attempts ($\approx$ 1000)). Figure 7 shows that StratDef works best across both datasets. Although the DT models perform adequately against DREBIN, they perform much worse for SLEIPNIR. For DREBIN, we generally observe that as the number of samples at training-time increases, the success rate increases. This supports the hypothesis that substitute models that are trained using a higher number of input-output relations of the target model are better representations of it. For DREBIN, the attacker achieves a 19% success rate against StratDef in the worst-case which is lower, hence better, than other defenses, and around 16% on average, still lower than the other defenses. Recall that StratDef is not currently strategized to deal with such an attack despite its better performance. As StratDef is cycling between models during predictions, we also observe variations in the attacker’s performance. For SLEIPNIR, the attacker is less successful, which is a theme we have seen previously. This is due to a more limited feature-space (i.e., the set of allowed perturbations for generating adversarial examples) and is reflected in the results for the black-box attack, where the attacker’s success drops considerably against the stronger defenses such as StratDef ($< 1\%$ success rate). However, the weaker decision tree models are evaded greatly, with success rates of 25+. StratDef makes use of the DT-AT-0.1 model in its strategy at this threat level and therefore suffers slightly in comparison to other models. In the more complex scenario involving DREBIN, StratDef offers superior performance against black-box attacks. For SLEIPNIR, we also observe that the attacker’s success decreases against voting after 200 samples. This is likely because the substitute model becomes noisier. As voting uses multiple models for a prediction, there may be some predictions that are output without a large majority for either class. This means training data for the substitute model becomes inaccurate, leading to poorer attack performance.

Fig. 9: Results of black-box attack against various defenses.

7 Conclusion

In this paper, we presented our strategic defense, StratDef, for defending against adversarial attacks for ML-based malware detection. We have demonstrated the superiority of StratDef over existing defenses across both Android and Windows malware. StratDef embraces the key design principles of a moving target defense and provides a complete framework for building a strategic ensemble defense using different heuristically-driven methods for determining what, how and when a defense system should move to achieve a high degree of adversarial robustness. We have illustrated the dynamic nature of StratDef, which offers flexible methods to promote model heterogeneity, adversarial robustness, and accurate predictions. Moreover, we have shown how StratDef can adapt to the threat level based on the information it has about its operating environment. Experimentally, we have demonstrated StratDef’s ability to achieve high levels of adversarial robustness across different threat levels without compromising on performance when compared with other defenses. Overall, we have demonstrated the ability to construct a strategic defense that can increase accuracy by 50+ whilst reducing the success of targeted attacks by increasing the uncertainty and complexity for the attacker.

The results in this paper motivate and provide evidence supporting a strategic MTD approach for dealing with adversarial examples in the malware detection domain. Beyond the work presented in this paper, multiple avenues exist for future work on strategic defenses in this domain. For example, we plan to investigate how to deal with black-box attacks even better. This may be achieved by adapting the defense strategy according to the current perceived threat levels that could be based on automated, stateful approaches \textsuperscript{[61]}, or on cyber-threat intelligence \textsuperscript{[56, 57]}.

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### APPENDIX A
ARCHITECTURE OF VANILLA MODELS

| Model                | Parameters                                      |
|----------------------|-------------------------------------------------|
| Decision Tree        | max_depth=5, min_samples_leaf=1                 |
| Neural Network       | 4 fully-connected layers (128 (Relu), 64 (Relu), 32 (Relu), 2 (Softmax)) |
| Random Forest        | random_state=0, max_depth=100                   |
| Support Vector Machine| Default LinearSVC with probability enabled     |

### APPENDIX B
STRATDEF STRATEGIES

5 attacker types, 2 datasets and 6 StratDef configurations, leads to 60 strategy vectors. For brevity, we only include some examples of the StratDef strategies for both datasets. For each strategy vector, the rows correspond to the models selected through our model selection methods (Best & Variety). Within each row, the probability of that model being selected at a particular attack intensity is listed.

#### TABLE 4: DREBIN, StratDef-Best-GT, Strong attacker

#### TABLE 5: DREBIN, StratDef-Best-Ranked, Strong attacker

#### TABLE 6: DREBIN, StratDef-Variety-GT, Weak attacker

#### TABLE 7: DREBIN, StratDef-Variety-Ranked, Random attacker

#### TABLE 8: SLEIPNIR, StratDef-Best-GT, Medium attacker

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### APPENDIX C
FPR OF MAJORITY VOTING VS. VETO VOTING

![Graph](image_url)

Fig. 10: Average FPR of Voting-Variety-Majority & Voting-Variety-Veto against the strong attacker across intensities.
APPENDIX D
EXTENDED RESULTS

We include all our results for experiments against each gray-box attacker. Due to space limitations, we limit our presentation of results to the following metrics: accuracy, F1, AUC and FPR.

Note that AUC and FPR require two classes. At \( \alpha = 1 \), there is only one class (malware) and therefore the values of these metrics are undefined or “nan” at this attack intensity. If these metrics are used in the consideration score, for \( \alpha = 1 \), we use average value of these metrics across all other attack intensities instead.

| Attack Method | Accuracy | F1 | AUC | FPR |
|---------------|----------|----|-----|-----|
| DT            | 0.952    | 0.9 | 0.846 | 0.744 |
| SVM           | 0.901    | 0.869 | 0.821 | 0.793 |
| NN-DD         | 0.965    | 0.911 | 0.843 | 0.799 |
| SecSVM        | 0.942    | 0.913 | 0.902 | 0.867 |

TABLE 9: DREBIN, Weak Attacker

| Attack Method | Accuracy | F1 | AUC | FPR |
|---------------|----------|----|-----|-----|
| DT-AT-0.001   | 0.913    | 0.884 | 0.865 | 0.892 |
| RF-AT-0.001   | 0.965    | 0.952 | 0.931 | 0.921 |
| NN-AT-0.001   | 0.948    | 0.877 | 0.802 | 0.755 |

TABLE 10: DREBIN, Medium Attacker
### TABLE 11: DREBIN, Strong Attacker

| Method          | Accuracy | F1   | AUC  | FPR  |
|-----------------|----------|------|------|------|
| DT              | 0.968    | 0.906| 0.852| 0.797|
| SVM             | 0.906    | 0.856| 0.799| 0.739|
| SVM-RFN         | 0.967    | 0.9  | 0.834| 0.764|
| DT-AT-0.1       | 0.949    | 0.861| 0.772| 0.68  |
| RF              | 0.94  | 0.872| 0.804| 0.735|
| NN              | 0.924    | 0.86 | 0.8  | 0.736|
| SecSVM          | 0.972    | 0.928| 0.891| 0.83  |
| StratDef-Best-GT| 0.972    | 0.918| 0.872| 0.828|
| StratDef-Best-Ranked | 0.972 | 0.902| 0.865| 0.848|
| StratDef-Variety-Ranked | 0.972 | 0.902| 0.865| 0.848|
| StratDef-Best-URS | 0.94  | 0.879| 0.836| 0.797|

### TABLE 12: DREBIN, Random Attacker

| Method          | Accuracy | F1   | AUC  | FPR  |
|-----------------|----------|------|------|------|
| DT              | 0.965    | 0.902| 0.837| 0.77  |
| SVM             | 0.903    | 0.851| 0.797| 0.739|
| SVM-RFN         | 0.962    | 0.9  | 0.834| 0.764|
| DT-AT-0.25      | 0.93     | 0.857| 0.799| 0.739|
| RF              | 0.93  | 0.857| 0.799| 0.739|
| NN              | 0.924    | 0.86 | 0.8  | 0.736|
| SecSVM          | 0.972    | 0.928| 0.891| 0.83  |
| StratDef-Best-GT| 0.972    | 0.918| 0.872| 0.828|
| StratDef-Best-Ranked | 0.972 | 0.902| 0.865| 0.848|
| StratDef-Variety-Ranked | 0.972 | 0.902| 0.865| 0.848|
| StratDef-Best-URS | 0.94  | 0.879| 0.836| 0.797|
| Model               | F1  | AUC  | FPR  |
|---------------------|-----|------|------|
| **DT**              | 0.901 | 0.886 | 0.881 |
| **RF**              | 0.953 | 0.918 | 0.913 |
| **NN**              | 0.923  | 0.925  | 0.921  |
| **DT-AT-0.001**     | 0.903  | 0.888  | 0.884  |
| **RF-AT-0.01**      | 0.964  | 0.969  | 0.966  |
| **SecSVM-AT-0.05**  | 0.916  | 0.835  | 0.756  |
| **DT-AT-0.25**      | 0.928  | 0.894  | 0.862  |
| **NN-AT-0.01**      | 0.923  | 0.925  | 0.921  |
| **NN-AT-0.1**       | 0.923  | 0.925  | 0.921  |
| **NN-AT-0.25**      | 0.923  | 0.925  | 0.921  |
| **StratDef-Variety-GT** | 0.928  | 0.937  | 0.941  |

TABLE 13: DREBIN, Universal Attacker

| Model               | F1  | AUC  | FPR  |
|---------------------|-----|------|------|
| **SLEIPNIR**        | 0.928  | 0.937  | 0.941  |

TABLE 14: SLEIPNIR, Weak Attacker
| Method          | 0   | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1   | Average |
|-----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|---------|
| DT              | 0.903 | 0.845 | 0.796 | 0.747 | 0.685 | 0.643 | 0.580 | 0.531 | 0.484 | 0.433 | 0.377 | 0.639 |
| NN-DD           | 0.906 | 0.853 | 0.815 | 0.776 | 0.728 | 0.703 | 0.658 | 0.632 | 0.613 | 0.592 | 0.560 | 0.535 |
| DT-AT-0.1       | 0.912 | 0.849 | 0.786 | 0.726 | 0.660 | 0.610 | 0.530 | 0.466 | 0.409 | 0.352 | 0.287 | 0.599 |
| RF-AT-0.05      | 0.913 | 0.853 | 0.798 | 0.747 | 0.697 | 0.661 | 0.598 | 0.556 | 0.503 | 0.462 | 0.427 | 0.398 |
| SecSVM-AT-0.01  | 0.904 | 0.846 | 0.798 | 0.748 | 0.687 | 0.646 | 0.583 | 0.534 | 0.487 | 0.436 | 0.381 | 0.641 |
| NN-DD           | 0.911 | 0.826 | 0.746 | 0.658 | 0.572 | 0.482 | 0.399 | 0.313 | 0.231 | 0.142 | 0.164 | 0.495 |
| SecSVM          | 0.913 | 0.83 | 0.752 | 0.669 | 0.585 | 0.499 | 0.424 | 0.345 | 0.274 | 0.213 | 0.164 | 0.495 |
| RF-AT-0.05      | 0.915 | 0.837 | 0.771 | 0.690 | 0.611 | 0.528 | 0.453 | 0.380 | 0.301 | 0.222 | 0.362 | 0.552 |
| SecSVM-AT-0.25  | 0.904 | 0.829 | 0.767 | 0.688 | 0.614 | 0.531 | 0.458 | 0.386 | 0.315 | 0.235 | 0.389 | 0.556 |
| SecSVM-AT-0.1   | 0.902 | 0.913 | 0.929 | 0.937 | 0.950 | 0.954 | 0.964 | 0.971 | 0.983 | 0.989 | 0.996 | 0.953 |
| SecSVM-AT-0.25  | 0.904 | 0.829 | 0.767 | 0.688 | 0.614 | 0.531 | 0.458 | 0.386 | 0.315 | 0.235 | 0.389 | 0.556 |
| SecSVM-AT-0.1   | 0.902 | 0.913 | 0.929 | 0.937 | 0.950 | 0.954 | 0.964 | 0.971 | 0.983 | 0.989 | 0.996 | 0.953 |

TABLE 15: SLEIPNIR, Medium Attacker

TABLE 16: SLEIPNIR, Strong Attacker
### TABLE 17: SLEIPNIR, Random Attacker

| Method          | F1    | AUC   | FPR  |
|-----------------|-------|-------|------|
| DT              | 0.877 | 0.857 | 0.836|
| SVM             | 0.875 | 0.863 | 0.84  |
| RF-RFN          | 0.915 | 0.85  | 0.788|
| NN-AT-0.001     | 0.906 | 0.854 | 0.801|
| StratDef-Best-Ranked | 0.921 | 0.909 | 0.897|
| NN-DD           | 0.883 | 0.889 | 0.888|
| DT-AT-0.05      | 0.886 | 0.886 | 0.906|
| RF-AT-0.01      | 0.925 | 0.933 | 0.936|
| NN-RFN          | 0.877 | 0.861 | 0.846|
| SVM             | 0.875 | 0.863 | 0.84  |
| RF-RFN          | 0.915 | 0.85  | 0.788|
| NN-AT-0.1       | 0.921 | 0.931 | 0.934|
| StratDef-Variety-GT | 0.91  | 0.899 | 0.884|

### TABLE 18: SLEIPNIR, Universal Attacker

| Method          | F1    | AUC   | FPR  |
|-----------------|-------|-------|------|
| DT              | 0.877 | 0.857 | 0.836|
| SVM             | 0.875 | 0.863 | 0.84  |
| RF-RFN          | 0.915 | 0.85  | 0.788|
| NN-AT-0.001     | 0.906 | 0.854 | 0.801|
| StratDef-Best-Ranked | 0.921 | 0.909 | 0.897|
| NN-DD           | 0.883 | 0.889 | 0.888|
| DT-AT-0.05      | 0.886 | 0.886 | 0.906|
| RF-AT-0.01      | 0.925 | 0.933 | 0.936|
| NN-RFN          | 0.877 | 0.861 | 0.846|
| SVM             | 0.875 | 0.863 | 0.84  |
| RF-RFN          | 0.915 | 0.85  | 0.788|
| NN-AT-0.1       | 0.921 | 0.931 | 0.934|
| StratDef-Variety-GT | 0.91  | 0.899 | 0.884|