Adversarial Learning in the Cyber Security Domain

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In recent years, machine learning algorithms, and more specially, deep learning algorithms, have been widely used in many fields, including cyber security. However, machine learning systems are vulnerable to adversarial attacks, and this limits the application of machine learning, especially in non-stationary, adversarial environments, such as the cyber security domain, where actual adversaries (e.g., malware developers) exist. This paper comprehensively summarizes the latest research on adversarial attacks against security solutions that are based on machine learning techniques and presents the risks they pose to cyber security solutions. First, we discuss the unique challenges of implementing end-to-end adversarial attacks in the cyber security domain. Following that, we define a unified taxonomy, where the adversarial attack methods are characterized based on their stage of occurrence, and the attacker’s goals and capabilities. Then, we categorize the applications of adversarial attack techniques in the cyber security domain. Finally, we use our taxonomy to shed light on gaps in the cyber security domain that have already been addressed in other adversarial learning domains and discuss their impact on future adversarial learning trends in the cyber security domain.

CCS Concepts:
- General and reference -> Surveys and overviews;

Additional Key Words and Phrases: adversarial learning; adversarial machine learning; evasion attacks; poisoning attacks; deep learning; adversarial examples; cyber security.

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1 INTRODUCTION

The growing use of machine learning, and more specially, deep learning, in fields like computer vision and natural language processing (NLP), has been accompanied by increased interest in the domain of adversarial learning, i.e., attacking and defending machine learning models algorithmically [55]. Of special interest are adversarial examples, which are samples modified in order to be misclassified by the attacked classifier.

Most of the research in adversarial learning has focused on the computer vision domain, and more specially, in the image recognition domain. This research has concentrated mainly on convolutional neural networks (CNNs), commonly used in the computer vision domain [3, 94]. However, in recent years, adversarial example generation methods have increasingly been utilized in other domains, including natural language processing (NLP; e.g., [37]). Some of these attacks have also been used in the cyber security domain (e.g., [104]). This domain is particularly interesting, because it is rife with adversaries, e.g., malware developers who want to evade machine and deep learning-based next generation.
anti-virus products, spam filters, etc.). Adversarial learning methods have already been executed against deep neural networks based on static analysis features [1].

The main goal of this paper is to illuminate the risks posed by adversarial learning to cyber security solutions that are based on machine learning techniques. This paper contains: (1) an in depth discussion about the unique challenges of adversarial learning in the cyber security domain (Section 2), (2) an overview of the state-of-the-art adversarial learning research papers in the cyber security domain, categorized by application (Section 5) and segmented according to our unified taxonomy (defined in Section 4), (3) a discussion of the possible future research directions (Section 6), including issues relating to existing defense methods (and the lack thereof), and (4) an introduction of the theoretical background of the adversarial methods used in the cyber security domain (Section 3).

The main contributions of this paper are as follows:

1. We focus on a wide range of adversarial learning applications in the cyber security domain (e.g., malware detection, speaker recognition, cyber-physical systems, etc.), introduce a new, unified taxonomy and illustrate how existing research fits into this taxonomy, providing a holistic overview of the field. In contrast, previous work focused mainly on specific domains, e.g., malware detection or network intrusion detection.

2. Using our taxonomy, we highlight research gaps in the cyber security domain that have already been addressed in other adversarial learning domains (e.g., Trojan neural networks in the image recognition domain) and discuss their impact on current and future adversarial learning trends in the cyber security domain.

3. We discuss the unique challenges that attackers and defenders face in the cyber security domain, which don’t exist in other domains (e.g., image recognition). For instance, in the cyber security domain the attacker must verify that the original functionality of the malicious adversarial example remains intact. Our discussion addresses the fundamental differences between adversarial attacks performed in the cyber security domain and those performed in other domains.

2 PRELIMINARY DISCUSSION: THE DIFFERENCES BETWEEN ADVERSARIAL ATTACKS IN THE COMPUTER VISION AND CYBER SECURITY DOMAINS

Most published adversarial attacks, including those published at academic cyber security conferences, have focused on the computer vision domain, e.g., generating an image of a cat that would be classified as a dog by the classifier. However, the cyber security domain (e.g., for malware detection) seems a more relevant domain for adversarial attacks, because in the computer vision domain, there is no concrete adversary (with a few exceptions, e.g., terrorists who want to tamper with the pedestrian detection systems of autonomous cars, etc.). In contrast, in the cyber security domain, there are actual adversaries with clear, targeted goals. Examples include ransomware developers who depend on the ability of their ransomware to evade anti-malware products that would prevent both the ransomware’s execution and the developers from collecting the ransom money, and other types of malware that need to steal user information (e.g., keyloggers), spread across the network (worms), or perform any other malicious functionality while remaining undetected.

A key step in defining an adversarial learning taxonomy suitable for the cyber security domain is answering the question: Given the obvious relevance of the cyber security domain to adversarial attacks, why do most adversarial learning researchers focus on computer vision? In addition to the fact that image recognition is a popular machine learning research topic, another major reason that researchers focus on adversarial learning in the computer vision domain rather than in the cyber security domain is that performing an end-to-end adversarial attack in the cyber security domain is more difficult than performing such an attack in the computer vision domain (although it is non-trivial there...
too [35]). The differences between adversarial attacks performed in the two domains and the challenges that arise in the cyber security domain are discussed in the subsections that follow.

2.1 There Is a Need to Keep The (Malicious) Functionality Intact in the Perturbed Sample

Any adversarial executable must preserve its malicious functionality after the sample’s modification. This is the main difference between the image classification and malware detection domains and likely poses the greatest challenge. In the image recognition domain, the adversary can change every pixel’s color (to a different valid color) without creating an “invalid picture” as part of the attack. However, in the cyber security domain, modifying an API call or arbitrary executable’s content byte value might cause the modified executable to perform a different functionality (e.g., modifying a WriteFile() call to a ReadFile()) or even crash (if you change an arbitrary byte in an opcode to an invalid opcode that would cause an exception). The same is true for network packets; perturbing a network packet in order to evade a network intrusion detection system (NIDS) while maintaining a valid packet structure is challenging.

In order to address this challenge, adversaries in the cyber security domain must implement their own methods (which are usually feature-specific) to modify features in a way that will not harm the functionality of the perturbed sample, whether it is an executable, a network packet, or something else. For instance, the adversarial attack used in Rosenberg et al. [104] generates a new malware PE with a modified API call trace in a functionality preserving manner.

2.2 There Are Many Feature Types

In the cyber security domain, classifiers usually use more than a single feature type as input (e.g., phishing detection using both URL and connected server properties in Shirazi et al. [114]). Some feature types are easier to modify without harming the executable’s functionality than others. For instance, in the adversarial attack used in Rosenberg et al. [104], appending printable strings to the end of a malware PE file is much easier than adding API calls to the PE file using a dedicated framework built for this purpose. In contrast, in an image adversarial attack, modifying each pixel has the same level of difficulty. The implications of this issue are discussed in Section 6.5.1.

2.3 Small Perturbations Are Not Applicable for Discrete Features

In the computer vision domain, gradient-based adversarial attacks, e.g., the fast gradient sign method (FGSM) (Section 3), generate minimal random modification to the input image in the direction that would most significantly impact the attacked classifier’s prediction. A ‘small modification’ (a.k.a. perturbation) can be, for example, changing a single pixel’s color to a very similar color: we can change a single pixel’s color from brown to black to fool the image classifier.

However, this logic of ‘small perturbation’ cannot be applied to many cyber security features. Consider a dynamic analysis classifier that uses API calls. An equivalent to changing a single pixel’s color would be to change a single API call to another API call. Even if we disregard what such modification would do to the executable’s functionality (mentioned in the previous subsection), would any of the following be considered a ‘small perturbation’ of the WriteFile() API call: (1) modifying it to a ReadFile() (a different operation for the same type of media) or (2) modifying it to RegSetValueEx() (a similar operation for a different type of media)? The use of discrete features (e.g., API calls) which are not continuous or ordinal severely limits the use of gradient-based attack methods (Section 3). The implications of this issue are discussed in Section 6.5.1.
2.4 Executables Are More Complex Than Images

An image used as input to an image classifier (usually a convolutional neural network, CNN) is represented as a fixed size matrix of pixel colors. If the actual image has different dimensions than the input matrix, the picture will usually be resized, clipped, or padded to fit the dimension limits.

An executable, on the other hand, has a variable length: executables can range in size from several kilobytes to several gigabytes. It is also unreasonable to expect a clipped executable to keep its original classification. Let’s assume we have a 100MB benign executable into which we inject a shellcode at a function near the end of the file. If the shellcode is clipped in order to fit the malware classifier’s dimensions, there is no reason that the file would be classified as malicious, because its benign variant would be clipped to the exact same input.

In addition, the execution path of an executable may depend on the input, and thus, the adversarial perturbation should support any possible input that malware may encounter when executed in the target machine.

While this is a challenge for malware classifier implementation, it also affects adversarial attacks against malware classifiers. Attacks in which you have a fixed input dimension, (e.g., a 28*28 matrix for MNIST images) are much easier to implement than attacks for which you need to consider the variable file size.

3 ADVERSARIAL LEARNING METHODS USED IN THE CYBER SECURITY DOMAIN

This section includes an overview of adversarial learning methods used in the cyber security domain which are inspired by attacks from other domains. Due to space limitations, this is not a complete list of the state-of-the-art prior work in other domains, such as image recognition or NLP. Only methods that have been used in the cyber security domain are specified. More comprehensive overviews relevant to other domains can be found, e.g., in Qiu et al. [94].

In [125] and [16], the search for adversarial examples is formalized as a similar minimization problem:

$$\arg_{r} \min f(x + r) \neq f(x) \text{ s.t. } x + r \in D$$

(1)

The input $x$, correctly classified by the classifier $f$, is perturbed with $r$, such that the resulting adversarial example $x + r$ remains in the input domain $D$ but is assigned a different label than $x$. To solve Equation 1, the constraint $f(x + r) \neq f(x)$ should be transformed into an optimizable formulation. Then, the Lagrange multiplier can be used to solve it. To do this, we define a loss function $Loss()$ to quantify this constraint. This loss function can be the same as the training loss, or different, e.g., hinge loss or cross-entropy loss. Each of the various methods in the subsections that follow attempt to solve Equation 1 in a different way, based on different knowledge that the attacker have about the attacked classifier.

Gradient-Based Attacks

In gradient-based attacks, adversarial perturbations are generated in the direction of the gradient, i.e., in the direction with the maximum effect on the classifier’s output (e.g., FGSM; Equation 4). Gradient-based attacks are effective but require adversarial knowledge about the targeted classifier’s gradients. Such attacks also require knowledge about the architecture of the attacked classifier and are therefore white-box attacks.

When dealing with malware classification tasks, differentiating between malicious ($f(x) = 1$) and benign ($f(x) = -1$), as done by SVM, Biggio et al. [16] suggested solving Equation 1 using gradient ascent. To minimize the size of the
perturbation and maximize the adversarial effect, the white-box perturbation should follow the gradient direction (i.e., the direction providing the greatest increase in confidence score from one label to another). Therefore, the perturbation \( r \) in each iteration is calculated as:

\[
\begin{align*}
    r &= \epsilon \nabla_x \text{Loss}_f(x + r, -1) \quad \text{s.t.} \quad f(x) = 1,
\end{align*}
\]

where \( \epsilon \) is a parameter controlling the magnitude of the perturbation introduced. By varying \( \epsilon \), this method can find an adversarial sample \( x + r \).

Szegedy et al. [125] views the (white-box) adversarial problem as a constrained optimization problem, i.e., find a minimum perturbation in the restricted sample space. The perturbation is obtained by using box-constrained L-BFGS to solve the following equation, where \( d \) is a term added for the Lagrange multiplier:

\[
\begin{align*}
    \arg_{r} \min_d (d * |r| + \text{Loss}_f(x + r, l)) \quad \text{s.t.} \quad x + r \in D,
\end{align*}
\]

(3)

Goodfellow et al. [43] introduced the white-box fast gradient sign method (FGSM). This method optimizes the \( L_\infty \) norm (i.e., reduces the maximum perturbation on any input feature) by taking a single step to each element of \( r \) in the direction opposite the gradient. The intuition behind this attack is to linearize the cost function \( \text{Loss}(\cdot) \) used to train a model \( f \) around the neighborhood of the training point \( x \) with a label \( l \) that the adversary wants to misclassify. Under this approximation:

\[
\begin{align*}
    r &= \epsilon \text{sign} (\nabla_x \text{Loss}_f(x, l)).
\end{align*}
\]

(4)

Kurakin et al. [70] extended research in this area, proposing the iterative gradient sign method (iGSM). As its name suggests, this method applies FGSM iteratively and clips pixel values of intermediate results after each step to ensure that they are close to the original image (the initial adversarial example is the original input):

\[
\begin{align*}
    x'_{n+1} &= \text{Clip} \left\{ x'_{n} + \epsilon \text{sign}(\nabla_x \text{Loss}_f(x'_{n}, l)) \right\};
\end{align*}
\]

(5)

The white-box Jacobian-based saliency map approach (JSMA) was introduced by Papernot et al. [87]. This method minimizes the \( L_0 \) norm by iteratively perturbing features of the input which have large adversarial saliency scores. Intuitively, this score reflects the adversarial goal of moving a sample away from its source class towards a chosen target class.

First, the adversary computes the Jacobian of the model: \( \frac{\partial f_j}{\partial x_i}(x) \), where component \((i, j)\) is the derivative of class \( j \) with respect to input feature \( i \). To compute the adversarial saliency map, the adversary then computes the following for each input feature \( i \):

\[
\begin{align*}
    S(x, t)[i] &= \begin{cases} 
        0 & \text{if } \frac{\partial f_j(x)}{\partial x_i} < 0 \text{ or } \sum_{j \neq t} \frac{\partial f_j(x)}{\partial x_i} > 0, \\
        \frac{\partial f_j(x)}{\partial x_i} & \text{otherwise}
    \end{cases},
\end{align*}
\]

(6)

where \( t \) is the target class that the adversary wants the machine learning model to assign. The adversary then selects the input feature \( i \) with the highest saliency score \( S(x, t)[i] \) and increases its value. This process is repeated until misclassification of the target class is achieved or the maximum number of perturbed features has been reached. This attack creates smaller perturbations with a higher computing cost than [43].
The Carlini-Wagner (C&W) attack [22] formulates the generation of adversarial examples as an optimization problem: find some small change $r$ that can be made to an input $x + r$ that will change its classification, such that the result is still in the valid range. They instantiate the distance metric with an $L_p$ norm (e.g., can either minimize the $L_2$, $L_0$, or $L_1$ distance metric), define the cost function $Loss()$ such that $Loss(x + r) \geq 0$ if and only if the model correctly classifies $x + r$ (i.e., gives it the same label that it gives $x$), and minimize the sum with a trade-off constant $c$ which is chosen by modified binary search:

$$\arg_r \min \left( ||r||_p + c \cdot Loss_f(x + r, t) \right) \text{ s.t. } x + r \in D,$$

(7)

where the cost function $Loss()$ maximizes the difference between the target class probability and the class with the highest probability. It is defined as:

$$\max \left( \arg_{i \in \mathbb{Z}} \max(f(x + r, i)) - f(x + r, t), -k \right),$$

(8)

where $k$ is a constant to control the confidence.

Moosavi-Dezfooli et al. [82] proposed the DeepFool adversarial method to find the shortest distance from the original input to the decision boundary of adversarial examples. DeepFool is an untargeted attack technique optimized for the $L_2$ distance metric. An iterative attack by linear approximation is proposed in order to overcome the nonlinearity of a high dimension. If $f$ is a binary differentiable classifier, an iterative method is used to approximate the perturbation by considering that $f$ is linearized around $x + r$ in each iteration. The minimal perturbation is provided by:

$$\arg_r \min (||r||_2) \text{ s.t. } f(x + r) + \nabla_x f(x + r)^T \cdot r = 0.$$

(9)

This result can be extended to a more general $L_p$ norm, $p \in [0, \infty)$. Madry et al. [79] proposed a projected gradient descent (PGD) based adversarial method to generate adversarial examples with minimized empirical risk and the trade-off of a high perturbation cost. The model’s empirical risk minimization (ERM) is defined as $E(x, y) \cdot D[Loss(x, y, \theta)]$, where $x$ is the original sample, and $y$ is the original label. By modifying the ERM definition by allowing the adversary to perturb the input $x$ by the scalar value $S$, ERM is represented by $\min_\theta \rho(\theta) : \rho(\theta) = E(x, y) \cdot D[\max_{S \in S} Loss(x + r, y, \theta)]$, where $\rho(\theta)$ denotes the objective function. Note that $x + r$ is updated in each iteration.

Chen et al. [23] presented the elastic net adversarial method (ENM). This method limits the total absolute perturbation across the input space, i.e., the $L_1$ norm. ENM produces adversarial examples by expanding an iterative $L_2$ attack with an $L_1$ regularizer.

Papernot et al. [88] presented a white-box adversarial example attack against RNNs. The adversary iterates over the words $x[i]$ in the review and modifies the words as follows:

$$x[i] = \arg \min_z ||sign(x[i] - z) - sign(J_f(x)[i, f(x)])|| \text{ s.t. } z \in D,$$

(10)

where $f(x)$ is the original model label for $x$, and $J_f(x)[i, j] = \frac{\partial}{\partial x_i} (x). sign(J_f(x)[i, f(x)])$ provides the direction one has to perturb each of the word embedding components in order to reduce the probability assigned to the current class and thus change the class assigned to the sentence. However, the set of legitimate word embeddings is finite. Thus, one cannot set the word embedding coordinates to any real value. Instead, one finds the word $z$ in dictionary $D$ such that the sign of the difference between the embeddings of $z$ and the original input word is closest to $sign(J_f(x)[i, f(x)])$. This
embedding takes the direction closest to the one indicated by the Jacobian as most impactful on the model’s prediction. By iteratively applying this heuristic to a word sequence, an adversarial input sequence that will be misclassified by the model is eventually found.

Score-Based Attacks

Score-based attacks are based on knowledge of the attacked classifier’s confidence score. Therefore, these are gray-box attacks.

The zeroth-order optimization (ZOO) attack was presented in [24]. ZOO uses hinge loss in Equation 8:

$$\max \left( \arg_{i,t} \max (\log(f(x + r, i)) - \log(f(x + r, t)), -k) \right).$$

(11)

ZOO uses the symmetric difference quotient to estimate the gradient and Hessian:

$$\frac{\partial f(x)}{\partial x_i} \approx \frac{f(x + h * e_i) - f(x - h * e_i)}{2h},$$

(12)

$$\frac{\partial^2 f(x)}{\partial x_i^2} \approx \frac{f(x + h * e_i) - 2f(x) + f(x - h * e_i)}{h^2},$$

(13)

where $e_i$ denotes the standard basis vector with the i-th component as one, and $h$ is a small constant.

Using Equations 11 and 12, the attacked classifier’s gradient can be numerically derived from the confidence scores of adjacent input points, and then a gradient-based attack is applied in the direction of maximum impact in order to generate an adversarial example.

Decision-Based Attacks

Decision-based attacks only use the label predicted by the attacked classifier. Thus, these are black-box attacks.

Generative Adversarial Network (GAN). An adversary can try to generate adversarial examples based on a GAN, a generative model introduced in [42] by Goodfellow et al. A GAN is designed to generate fake samples that cannot be distinguished from the original samples. A GAN is composed of two components: a discriminator and a generator. The generator is a generative neural network used to generate samples. The discriminator is a binary classifier used to determine whether the generated samples are real or fake. The discriminator and generator are alternately trained so that the generator can generate valid adversarial records. Assuming we have the original sample set $x$ with distribution $p_r$ and input noise variables $z$ with distribution $p_z$, $G$ is a generative multilayer perception function with parameter $g$ that generates fake samples $G(z)$, and $D$ is a discriminative multilayer perception function with parameter $d$ that outputs $D(x)$, which represents the probability that model $D$ correctly distinguishes fake samples from the original samples. $D$ and $G$ play the following two player minimax game with the value function $V(G; D)$:

$$\min_G \max_D V(G, D) = \frac{E}{X \sim p_r} [\log(D(X))] + \frac{E}{Z \sim p_z} [\log(1 - D(G(Z)))).$$

(14)

In this competing fashion, a GAN is capable of generating raw data samples that look close to the real data.

The Transferability Property. Many black-box attacks presented in this paper (e.g., [104, 115, 144]) rely on the concept of adversarial example transferability presented in [125]: Adversarial examples crafted against one model are also likely to be effective against other models. This transferability property holds even when the models are trained on different
datasets. This means that the adversary can train a surrogate model, which has decision boundaries similar to those of the original model, and perform a white-box attack against it. Adversarial examples that successfully fool the surrogate model would most likely fool the original model as well [86].

The transferability between DNNs and other models, such as decision tree and SVM models, was examined in [89]. A study of the transferability property using large models and a large-scale dataset, was conducted in [77], showing that while transferable non-targeted adversarial examples are easy to find, targeted adversarial examples rarely transfer with their target labels. However, for binary classifiers (commonly used in the cyber security domain), targeted and non-targeted attacks are the same.

The reasons for the transferability are unknown, but a recent study [58] suggested that adversarial vulnerability is not “necessarily tied to the standard training framework but is rather a property of the dataset (due to representation learning of non-robust features)”; this also clarifies why transferability happens regardless of the classifier architecture. This can also explain why transferability is applicable to training phase attacks (e.g., poisoning attacks) [83].

4 TAXONOMY

Adversarial learning in the cyber security domain is the modeling of non-stationary adversarial settings like spam filtering or malware detection, where a malicious adversary can carefully manipulate (or perturb) the input data, exploiting specific vulnerabilities of learning algorithms in order to compromise the (targeted) machine learning system’s security.

A taxonomy for the adversarial domain in general exists (e.g., Barreno et al. [13]) and inspired our taxonomy. However, the cyber security domain has a few unique challenges (described in the previous section), necessitating a dedicated taxonomy to categorize the existing attacks. Therefore, our taxonomy contains several new parts, e.g., the attack’s output, attack’s targeting, and perturbed features.

A chronological overview of our taxonomy is shown in Figure 1. The attacks are categorized based on seven distinct attack characteristics, which are sorted by four chronological phases of the attack:

1) Threat Model - The attacker’s knowledge and capabilities, known prior to the attack. The threat model characteristics include the training set access and attacker’s knowledge.

2) Attack Type - These characteristics are a part of the attack implementation. The attack type characteristics include the attacker’s goals, the targeted phase, and the attack’s targeting.

3) The features modified (or perturbed) in the attack.

4) The attack’s output.

A detailed overview of our taxonomy, including possible values for the seven characteristics, is shown in Figure 2. The seven attack characteristics are described in the subsections that follow.

We include these characteristics in our taxonomy because they possess the following attributes:

1) The characteristics are specific to the cyber domain (e.g., the perturbed features and attack’s output characteristics).
2) The characteristics are particularly relevant to the threat model, which plays a much more critical role in the cyber security domain where white-box attack are less valuable than in other domains; this is the case, because in the cyber security domain, the knowledge of adversaries about the classifier’s architecture is usually very limited (e.g., the attacker’s knowledge, attacker’s training set access, and targeted phase characteristics).

3) The characteristics highlight research which exists in other domains of adversarial learning which is missing in the cyber security domain (e.g., the attack’s targeting characteristic). We discuss these gaps in Section 6.

4) The characteristics exist in many domains but are more important in the cyber security domain. For instance, availability attacks (which is part of the attacker’s goal characteristic) are of limited use in other domains, but are very relevant in the cyber security domain.

4.1 Attacker’s Goals

This attack characteristic is sometimes considered part of the attack type (see Section 4). An attacker aims to achieve one or more of the following goals (a.k.a. the CIA triad): (1) Confidentiality - Acquire private information by querying the machine learning system, e.g., reverse engineering the classifier’s model [129], (2) Integrity - Cause the machine learning system to perform incorrectly for some or all input. For example, to cause a machine learning-based malware classifier to misclassify a malware sample as benign [119], and (3) Availability - Cause a machine learning system to
become unavailable or block regular use of the system. For instance, to generate malicious sessions which have many of the features of regular traffic, causing the system to classify legitimate traffic sessions as malicious and block legitimate traffic [28].

4.2 Attacker’s Knowledge

This attack characteristic is sometimes considered part of the threat model. Attacks vary based on the amount of knowledge the adversary has about the classifier he/she is trying to subvert: (1) **Black-box attack** - Requires no knowledge about the model beyond the ability to query it as a black-box (a.k.a. the oracle model), i.e., providing input and obtaining the output classification, (2) **Gray-box attack** - Requires some (limited) degree of knowledge about the targeted classifier. Usually this knowledge consists of the features monitored by the classifier, but sometimes it is other incomplete pieces of information, like the output of the hidden layers of the classifier or the confidence score (and not just the class label) provided by the classifier, (3) **White-box attack** - The adversary has knowledge about the model architecture and even the hyperparameters used to train the model, and (4) **Transparent-box attack** - In this case, the adversary has complete knowledge about the system, including both white-box knowledge and knowledge about the defense methods used by the defender (see Section 6.5). Such knowledge can assist the attacker in choosing an adaptive attack that would bypass the specific defense mechanism (e.g., Tramer et al. [128]).

While white-box attacks tend to be more efficient than black-box attacks (sometimes by an order of magnitude [100]), the required knowledge is rarely available in real-world use cases. However, white-box knowledge can be gained either through internal knowledge or using a staged attack to reverse engineer the model beforehand [129]. Each of the attacks (black-box, gray-box, etc.) has a query-limited variant in which the adversary has only a limited number of queries (in each query the adversary inserts input to the classifier and obtains its classification label), and not an unlimited amount of queries, as in the variants mentioned above. A query-limited variant is relevant in the cases of cloud security services (e.g., [102]). In such a service, the attacker pays for every query of the target classifier and therefore aims to minimize the number of queries made to the cloud service when performing an attack. Another reason for minimizing the number of queries is that many queries from the same computer might arouse suspicion of an adversarial attack attempt, causing the cloud service to stop responding to those queries. Such cases require query-efficient attacks.

4.3 Attacker’s Training Set Access

Another important characteristic of an attack, sometimes considered part of the threat model, is the access the adversary has to the training set used by the classifier (as opposed to access to the model itself, mentioned in the previous subsection): (1) **None** - no access to the training set, (2) **Read** data from the training set (entirely or partially), (3) **Add** new samples to the training set, and (4) **Modify** existing samples (the ability to modify either all features or only specific features, e.g., the label). For instance, poisoning attacks require **add or modify** permissions.

4.4 Targeted Phase

This attack characteristic is sometimes considered part of the attack’s type. Adversarial attacks against machine learning systems occur in two main phases of the machine learning process: (1) **Training phase attack** - This attack aims to introduce vulnerabilities (to be exploited in the classification phase) by manipulating training data during the training phase. For instance, a **poisoning attack** can be performed by inserting crafted malicious samples labeled as benign to the training set as part of the baseline training phase of a classifier, (2) **Inference phase attack** - This attack aims to find and subsequently exploit vulnerabilities in the classification phase. In this phase, the attacker only modifies samples from
the test set. For example, an *evasion attack* involves modifying the analyzed malicious sample’s features in order to evade detection by the model. Such inputs are called *adversarial examples*.

Note that attacks on online learning systems (for instance, anomaly detection systems [30]) combine both training phase and inference phase attacks: the attack is an evasion attack, but if it succeeds, the classifier learns that this traffic is legitimate, making such attacks harder for the system to detect in the future (i.e., there is a poisoning effect). Such attacks would be termed inference attacks in this paper, since in this case, the poisoning aspect is usually a by-product and is not the attacker’s main goal. Moreover, even if the poisoning aspect is important to the attacker, it would usually be successful only if the evasion attack works, so evasion is the primary goal of the attacker in any case.

### 4.5 Attack’s Targeting

This characteristic is sometimes considered a part of the attack’s type. Each attack has a different target, defining the trigger conditions or the desired effect on the classifier: (1) *Label-indiscriminate attack* - Always minimizes the probability of correctly classifying a perturbed sample (the adversarial example), (2) *Label-targeted attack* - Always maximizes the probability of a specific class to be predicted for the adversarial example (different from the predicted class for the unperturbed sample), and (3) *Feature-targeted attack* - The malicious behavior of these attacks are only activated by inputs containing an attack trigger, which might be the existence of a specific input feature or group of features’ values in the adversarial example.

Attacks can be both feature and label-targeted. Note that in the cyber security domain, many classifiers are binary (i.e., they have two output classes: malicious and benign, spam and ham, anomalous or not, etc.). For binary classifiers, label-indiscriminate and label-targeted attacks are the same, because in these cases, minimizing the probability of the current class (label-indiscriminate attack) is equivalent to maximizing the probability of the only other possible class.

### 4.6 Perturbed Features

As mentioned in Section 2.2, in the cyber security domain classifiers and other machine learning systems often use more than one feature type. Thus, attackers who want to subvert those systems should consider modifying more than a single feature type. We can therefore characterize the different adversarial attacks in the cyber security domain by the features being modified/perturbed or added. Note that the same feature type might be modified differently depending on the sample format. For instance, modifying a printable string inside a PE file might be more challenging than modifying a word within the content of an email content, although the feature type is the same. Thus, this classification is not simply a feature type, but a tuple of feature type and sample format, for instance: printable strings inside a PE file. The following is a *non-exclusive* list (Rosenberg et al. [101] alone contains 2381 features, so the full list cannot be provided here) of such tuples used in the papers reviewed in our research: PCAP (network session) statistical features (e.g., number of SYN requests in a certain time window), PCAP header (e.g., IP or UDP) fields, PE header fields, printable strings inside a PE file, binary bytes inside a PE file, PE executed API calls (during a dynamic analysis of the PE file), words inside an email or characters inside a URL.

### 4.7 Attack’s Output

As discussed in Section 2.1, and in contrast to image-based attacks, most adversarial attacks in the cyber domain require the modification of a feature’s values. While in some domains, such as spam detection, modifying a word in an email is non-destructive, modifying, e.g., a field in a PE header metadata might cause an unrunnable PE file. Thus, there are two type of attacks: (1) *Feature-vector attack* - Such attacks obtain a feature vector as an input and output a perturbed
feature vector. However, such an attack doesn’t generate a sample which can be used by the attacker and is usually only a hypothetical attack, and (2) End-to-end attack - This attack generates a functional sample as an output. Thus, this is a concrete real-life attack. Such attacks were reviewed in Pierazzi et al. [92]. This category is further divided into many subgroups based on the sample type produced, e.g., a valid and runnable PE file, a phishing URL, a spam email, etc.

For instance, most traffic anomaly detection attacks reviewed in this paper are feature vector attacks. They use statistical features which aggregate packet metadata, but don’t demonstrate how to generate the perturbed packet. In contrast, the attack used by Rosenberg et al. [104], in which API calls are added to a malicious process, uses a custom framework that generates a new binary that adds those API calls; thus, the attack in [104] is an end-to-end attack. In some image-based domains, e.g., face recognition systems (Section 5.6.1), end-to-end attacks can be further categorized as those that generate images (e.g., [78]) and those that generate physical elements that can be used to generate multiple relevant images (e.g., [113]).

5 CYBER APPLICATIONS OF ADVERSARIAL LEARNING METHODS

Our paper addresses adversarial attacks in the cyber security domain. An overview of this section is provided in Tables 1-6. The attacked classifier abbreviations are specified in Appendix A. The attack type includes the attacker’s goals, the targeted phase, and the attack’s targeting characteristics. The threat model includes the attacker’s knowledge and training set access characteristics. Unless otherwise mentioned, a gray-box attack requires knowledge of the attacked classifier’s features; in addition, the attack’s targeting is label-indiscriminate, and the attacker’s training set access is none. Some of the columns are not a part of our taxonomy (Section 4) but provide additional relevant information helpful for understanding the attacks, such as the attacked classifiers.

Each of the following subsections represents a specific cyber security domain/application that uses adversarial learning and discusses the adversarial learning methods used in this domain. Due to space limitations, this review paper only covers the state of the art in the abovementioned areas and not all adversarial attacks, especially in large and diverse domains, such as biometric or cyber-physical systems. The mathematical background for the deep learning classifiers is provided in Appendix A, and the mathematical background for the commonly used adversarial learning attacks in the cyber security domain is provided in Section 3.

Note that while the classifiers the attacker tries to subvert are mentioned briefly, in order to provide the context for understanding the attack, a complete list of the state-of-the-art prior work is not shown due to space limits. A more comprehensive list can be found, e.g., in Berman et al. [15]. Cases where an adversarial attack does not exist for a specific application type are omitted. This paper also does not review adversarial attacks in non-cyber domains, such as image recognition (with the exception of face recognition in Section 5.6.1, which is cyber related). It also does not cover papers related to cyber security, but not to adversarial learning, such as the use of machine learning to bypass CAPTCHA.

5.1 Malware Detection and Classification

Next generation anti-malware products, such as Cylance, CrowdStrike, SentinelOne, and Microsoft ATP use machine and deep learning models instead of signatures and heuristics, allowing them to detect unseen and unsigned malware but also leaving them open to attacks against such models.

Malware classifiers can either use static features gathered without running the code (e.g., n-gram byte sequences, strings, or structural features of the inspected code) or dynamic features (e.g., CPU usage) collected during the inspected code’s execution.
While using static analysis provides a performance advantage, it has a major disadvantage: Since the code isn’t executed, the analyzed code might not reveal its “true features.” For example, when looking for specific strings in the file, one might not be able to catch polymorphic malware, in which those features are either encrypted or packed, and decrypted only during runtime by a specific bootstrap code. Fileless attacks (code injection, process hollowing, etc.) are also a problem for static analysis. Thus, dynamic features, extracted at runtime, can be used. The most prominent dynamic features that can be collected during malware execution are the sequences of API calls ([62]), particularly those made to the OS, which are termed system calls. Those system calls characterize the software behavior and are harder to obfuscate during execution time without harming the functionality of the code. The machine learning techniques (and thus the attacks on them) can be divided into two groups: traditional (or shallow) machine learning and deep learning techniques. Table 1 summarizes the attacks in the malware detection subdomain.

5.1.1 Attacking Traditional (Shallow) Machine Learning Malware Classifiers. Srndić and Laskov [119] implemented an inference integrity gray-box evasion attack against PDFrate, a random forest classifier used for the static analysis of malicious PDF files, which utilizes PDF structural features, e.g., the number of embedded images or binary streams within the PDF. The attack used either a mimicry attack in which features were added to the malicious PDF to make it “feature-wise similar” to a benign sample or created an SVM representation of the classifier and subverted it using a method that follows the gradient of the weighted sum of the classifier’s decision function and the estimated density function of benign examples. This ensures that the final result lies close to the region populated by real benign examples. The density function must be estimated beforehand, using the standard techniques of kernel density estimation, and then the transferability property is used to attack the original PDFrate classifier using the same PDF file. Li et al. [73] performed an inference integrity gray-box attack against the same classifier by using GAN-generated feature vectors and transforming them back into PDF files.

Ming et al. [80] used an inference integrity replacement attack, replacing API calls with different functionality preserving API subsequences (so gray-box knowledge about the monitored APIs is required) to modify the malware code. They utilized a system call dependence graph (SCDG) with the graph edit distance and Jaccard index as clustering parameters of different malware variants and used several SCDG transformations on their malware source code to cause the malware to be misclassified. Their transformations can cause similar malware variants to be classified as a different cluster, but the authors didn’t show that the attack can cause malware to be classified (or clustered) as a benign program, which is usually the attacker’s main goal. Xu et al. [139] also implemented an inference integrity gray-box attack against a SCDG-based APK malware classifier, using n-strongest nodes and FGSM (see Section 3) methods.

Suciu et al. [123] and Chen et al. [25] used a training integrity poisoning attack against a linear SVM classifier trained on the Drebin dataset [9] for Android malware detection. This attack requires gray-box knowledge of the classifier’s features and add training set access. The poisoning was done by adding static features (permissions, API calls, URL requests) from the target to existing benign instances.

Munoz-Gonzalez et al. [83] used a training integrity poisoning attack of logistic regression, MLP, and ADALINE classifiers for spam and ransomware detection, by using back-gradient optimization. This attack requires gray-box knowledge of the classifier’s features and training set add and read access. A substitute model is built and poisoned, and the poisoned samples are effective against the attacked classifier as well, due to the transferability property.

Dang et al. [31] utilized the rate of feature modifications from a malicious sample and a benign known sample as the score and used a hill climbing approach to minimize this score, bypassing SVM and random forest PDF malware
| Citation | Year | Attacked Classifier | Attack Type | Attack’s Output | Threat Model | Perturbed Features |
|----------|------|---------------------|-------------|----------------|--------------|-------------------|
| [73, 119]| 2020 | RF                  | Inference integrity | PDF file (end-to-end) | Gray-box | Static structural PDF features |
| [80]     | 2015 | SCDG                | Inference integrity | PE file (end-to-end) | Gray-box | Executed API calls |
| [123]    | 2018 | SVM                 | Training integrity | Feature vector | Gray-box; add training set access | Static Android manifest features |
| [31]     | 2017 | SVM, RF.            | Inference integrity | PDF file (end-to-end) | Query-limited gray-box | Static structural PDF features |
| [6]      | 2018 | GBDT                | Inference integrity | PE file (end-to-end) | Black-box | Operations (e.g., packing) performed on a PE file |
| [45]     | 2017 | FC DNN              | Inference integrity | Feature vector | White-box | Static Android manifest features |
| [139]    | 2020 | SCDG                | Inference integrity | Feature vector | Gray-box | Static Android manifest features |
| [63, 67] | 2018 | 1D CNN              | Inference integrity | PE file (end-to-end) | White-box | PE file’s raw bytes |
| [122]    | 2018 | 1D CNN              | Inference integrity | PE file (end-to-end) | Black-box | PE file’s raw bytes |
| [101]    | 2020 | GBDT, FC DNN        | Inference integrity | PE file (end-to-end) | Black-box | PE header metadata |
| [52]     | 2017 | RF, LR, DT, SVM, MLP| Inference integrity | Feature vector | Gray-box | API call unigrams |
| [140]    | 2016 | SVM, RF, CNN        | Inference integrity | PDF file (end-to-end) | Gray-box | Static structural PDF features |
| [76]     | 2019 | FC DNN, LR, DT, RF | Inference integrity | Feature vector | Gray-box | Static Android manifest features |
| [2]      | 2019 | CNN                 | Inference integrity | Feature vector | White-box | CFG features |
| [51]     | 2017 | LSTM                | Inference integrity | Feature vector | Gray-box | Executed API calls |
| [104]    | 2018 | LSTM, GRU, FC DNN, 1D CNN, RF, SVM, LR, GBDT | Inference integrity | PE file (end-to-end) | Gray-box | Executed API calls, printable strings |
| [102]    | 2018 | LSTM, GRU, FC DNN, 1D CNN, RF, SVM, LR, GBDT | Inference integrity | PE file (end-to-end) | Query-limited gray-box | Executed API calls, printable strings |
classifiers based on static features in a query-efficient manner. Thus, their inference integrity attack is a query-limited gray-box attack.

In Anderson et al. [6], the features used by the gradient boosted decision tree classifier included PE header metadata, section metadata, and import/export table metadata. In [6], an inference integrity black-box attack which trains a reinforcement learning agent was presented. The agent is equipped with a set of operations (such as packing) that it may perform on the PE file. The reward function was the evasion rate. Through a series of games played against the attacked classifier, the agent learns which sequences of operations are likely to result in detection evasion for any given malware sample. The perturbed samples that bypassed the classifier were uploaded to VirusTotal and scanned by 65 anti-malware products. Those samples were detected as malicious by 50% of anti-malware products that detected the original, unperturbed samples. However, unlike other attacks, this attack’s effectiveness is less than 25% (as opposed to 90% for most other adversarial attacks), showing that work is still needed in order for this approach to be practical in real-life use cases.

5.1.2 Attacking Deep Neural Network Malware Classifiers. Rosenberg et al. [101] used the same dataset and PE structural features as [6] to train a substitute FC DNN model and used explainable machine learning algorithms (e.g., integrated gradients) to detect which of the 2400 features have high impact on the malware classification and can also be modified without harming the executable’s functionality (e.g., file timestamp). These features were modified by a gray-box inference integrity attack, and the mutated malware bypassed not only the substitute model but also the target GBDT classifier, which used a different subset of samples and features.

Grosse et al. [45] presented a white-box inference integrity attack against an Android fully connected DNN malware classifier. The static features used were from the AndroidManifest.xml file, including permissions, suspicious API calls, activities, etc. The attack is a discrete FGSM (Section 3) variant, which is performed iteratively in two steps until a benign classification is achieved: (1) Compute the gradient of the white-box model with respect to the binary feature vector \( x \). (2) Find the element in \( x \) whose modification from zero to one (i.e., only feature addition and not removal) would cause the maximum change in the benign score and add this manifest feature to the adversarial example.

Kreuk et al. [67] implemented an inference integrity attack against MalConv, a 1D CNN, using the file’s raw byte content as features (Raff et al. [96]). The additional bytes are selected by the FGSM method (see Section 3) and are inserted between the file’s sections. Kolosnjaji et al. [63] implemented a similar attack and also analyzed the bytes which are the most impactful features (and are therefore added by the attack), showing that a large portion of them are part of the PE header metadata. Suciu et al. [122] transformed this white-box gradient-based attack to a black-box decision-based attack by appending bytes from the beginning of benign files, especially from their PE headers, which, as shown in [63], are prominent features.

Hu and Tan [52] perturbed static API call unigrams using a gray-box inference integrity attack. If \( n \) API types are used, the feature vector dimension is \( n \). A generative adversarial network (GAN; Appendix A) was trained, where the discriminator simulates the malware classifier while the generator tries to generate adversarial samples that would be classified as benign by the discriminator, which uses labels from the black-box model (a random forest, logistic regression, decision tree, linear SVM, MLP, or an ensemble of all of these). However, this is a feature vector attack and not an end-to-end attack: the way to generate an executable with the perturbed API call trace was not presented.

Xu et al. [140] generated adversarial examples that bypass PDF malware classifiers, by modifying static PDF features. This was done using an inference integrity genetic algorithm (GA), where the fitness of the genetic variants is defined in terms of the attacked classifier’s confidence score. The GA is computationally expensive and was evaluated against...
SVM, random forest, and CNN classifiers using static PDF structural features. This gray-box attack requires knowledge of both the classifier’s features and the attacked classifier’s confidence score.

Liu et al. [76] used the same approach to bypass an Android malware detector for IoT devices. The bypassed fully connected DNN, logistic regression, decision tree, and random forest classifiers were trained using the Drebin dataset.

Abusnaina et al. [2] trained an IoT malware detection CNN classifier using graph-based features (e.g., shortest path, density, number of edges and nodes, etc.) from the control-flow graph (CFG) of the malware disassembly. They used white-box attacks: C&W, DeepFool, FGSM, JSMA (see Section 3), the momentum iterative method (MIM), projected gradient descent (PGD), and the virtual adversarial method (VAM). They also added their own attack, graph embedding, and augmentation, which adds a CFG of a benign sample to the CFG of a malicious sample via source code concatenation.

Hu and Tan [51] proposed a gray-box inference integrity attack using an RNN GAN to generate invalid APIs and inserted them into the original API sequences to bypass an LSTM classifier trained on the API call trace of the malware. A substitute RNN is trained to fit the targeted RNN. Gumbel-Softmax, a one-hot continuous distribution estimator, was used to smooth the API symbols and deliver gradient information between the generative RNN and the substitute RNN. Null APIs were added, but while they were omitted to make the generated adversarial sequence shorter, they remained in the gradient calculation of the loss function. This decreases the attack’s effectiveness, since the substitute model is used to classify the Gumbel-Softmax output, including the null APIs’ estimated gradients, so it doesn’t simulate the malware classifier exactly. The gray-box attack output is a feature vector of the API call sequence that might harm the malware functionality (e.g., by inserting the ExitProcess() API call in the middle of the malware code).

Rosenberg et al. [104] presented a gray-box inference integrity attack that adds API calls to an API call trace used as input to an RNN malware classifier in order to bypass a classifier trained on the API call trace of the malware. A GRU substitute model was created and attacked, and the transferability property was used to attack the original classifier. The authors extended their attack to hybrid classifiers, combining static and dynamic features and attacking each feature type in turn. The target models were LSTM variants, GRUs, conventional RNNs, bidirectional and deep variants, and non-RNN classifiers (including both feedforward networks, like fully connected DNNs and 1D CNNs, and traditional machine learning classifiers, such as SVM, random forest, logistic regression, and gradient boosted decision tree). The authors presented an end-to-end framework that creates a new malware executable without access to the malware source code.

A subsequent work ([102]) presented two query-limited gray-box inference integrity attacks against the same classifiers, based on benign perturbations generated using a GAN that was trained on benign samples. One of the gray-box attack variants requires the adversary to know which API calls are being monitored, and the other also requires the adversary to know the confidence score of the attacked classifier in order to operate an evolutionary algorithm to optimize the perturbation search and reduce the number of queries used. This attack is generic for every camouflaged malware and doesn’t require a per malware predeployment phase to generate the adversarial sequence (either using a GAN, as in [51], or a substitute model, as in [104]). Moreover, the generation is done at runtime, making it more generic and easier to deploy.

5.2 URL Detection

Every Web page has an address which is termed a uniform resource locator (URL). A URL begins with the protocol used to access the page. The fully qualified domain name (FQDN) identifies the server hosting the Web page. It consists of a registered domain name (RDN) and a prefix referred to as a subdomain. An attacker can gain full control of the
Table 2. Comparison of Adversarial Learning Approaches in URL Detection

| Citation | Year | Attacked Classifier | Attack Type | Attack’s Output | Threat Model | Perturbed Features |
|----------|------|---------------------|-------------|-----------------|--------------|-------------------|
| [12]     | 2018 | LSTM                | Inference integrity | URL (end-to-end) | Gray-box | URL characters |
| [114]    | 2019 | State-of-the-art phishing classifiers | Inference integrity | Feature vector | Gray-box | All features used by the classifiers |
| [4]      | 2020 | RF, NN, DT, LR, SVM | Inference integrity | URL (end-to-end) | Black-box | URL characters |
| [7]      | 2016 | RF                  | Inference integrity | URL (end-to-end) | Black-box | URL characters |
| [115]    | 2019 | CNN, LSTM, BLSTM    | Inference integrity | URL (end-to-end) | Black-box | URL characters |

Subdomains and can set them to any value. The RDN is constrained, since it has to be registered with a domain name registrar. The URL may also have a path and query components which also can be changed by the phisher at will.

Consider this URL example: https://www.amazon.co.uk/ap/signin?encoding=UTF8. We can identify the following components: protocol = https; FQDN = www.amazon.co.uk; RDN = amazon.co.uk; path and query = /ap/signin?encoding=UTF8. Table 2 summarizes the attacks in the URL detection subdomain.

Since URLs can be quite long, URL shortening services have started to appear. In addition to shortening the URL, these services also obfuscate them.

5.2.1 Phishing URL Detection. Phishing refers to the class of attacks where a victim is lured to a fake Web page masquerading as a target website and is deceived into disclosing personal data or credentials. Phishing URLs seem like legitimate URLs and redirect users to phishing web pages, which mimic the look and feel of the phishing web pages’ target websites (e.g., a bank website), in the hopes that the user will enter his/her personal information (e.g., password).

Bashen et al. [12] performed an inference integrity attack to evade a character-level LSTM-based phishing URL classifier ([11]) by concatenating the effective URLs from historical attacks (thus, this is a gray-box attack). Then, from this full text, sentences of a fixed length were created. An LSTM model used those sentences as a training set in order to generate the next character. After the model generated a full prose text, it was divided by http structure delimiters to produce a list of pseudo URLs. Each pseudo URL was assigned a compromised domain, such that the synthetic URLs take the form: http://+compromised_domain+pseudo_URL.

Shirazi et al. [114] generated adversarial examples using all possible combinations of the values of the features (e.g., website reputation) used by state-of-the-art phishing classifiers, such as [131]. However, this attack requires knowledge about the features being used by the classifier, making it a gray-box inference integrity attack.

Phishing URLs were generated by a text GAN in [5, 130], in order to augment the phishing URL classifier’s training set and improve its accuracy. AlEroud and Karabatis [4] used the generated phishing URLs as adversarial examples in an inference integrity attack, in order to bypass the attacked classifier.

5.2.2 Domain Generation Algorithm (DGA) URL Detection. DGAs are commonly used malware tools that generate large numbers of domain names that can be used for difficult to track communications with command and control...
servers operated by the attacker. The large number of varying domain names makes it difficult to block malicious domains using standard techniques such as blacklisting or sinkholing. DGAs are used in a variety of cyber attacks, including ransomware, spam campaigns, theft of personal data, and implementation of distributed denial-of-service (DDoS) attacks. DGAs allow malware to generate any number of domain names daily, based on a seed that is shared by the malware and the threat actor, allowing both to synchronize the generation of domain names.

Anderson et al. [7] performed an inference integrity black-box attack that used a GAN to produce domain names that current DGA classifiers would have difficulty identifying. The generator was then used to create synthetic data on which new models were trained. This is done by building a neural language architecture, a method of encoding language in a numerical format, using LSTM layers to act as an autoencoder. This is then repurposed, such that the encoder (which takes in domain names and outputs an embedding that converts a language into a numerical format) acts as the discriminator, and the decoder (which takes in the embedding and outputs the domain name) acts as the generator. Anderson et al. attacked a random forest classifier trained on features defined in [8, 107, 141, 142]. The features of the random forest DGA classifier are unknown to the attacker. They include: length of domain name, entropy of character distribution in the domain name, vowel to consonant ratio, Alexa top 1M n-gram frequency distribution co-occurrence count, where n = 3, 4, or 5, n-gram normality score, and meaningful character ratio.

Sidi et al. [115] used a black-box inference integrity attack, training a substitute model to simulate the DGA classifier on a list of publicly available DGA URLs. Then that attacker iterates over every character in the DGA URL. In each iteration, the results of the feedforward pass of the substitute model are used to compute the loss with regard to the benign class. The attacker performs a single backpropagation step on the loss in order to acquire the Jacobian-based saliency map, which is a matrix that assigns every feature in the input URL a gradient value (JSMA; see Section 3). Features (characters) with higher gradient values in the JSMA would have a more significant (salient) effect on the misclassification of the input, and thus each character would be modified in turn, making the substitute model’s benign score higher. Finally, URLs that evade detection by the substitute model would also evade detection by the target DGA classifier, due to the transferability property (see Section 3).

5.3 Network Intrusion Detection

A network intrusion detection system (NIDS) is a security system commonly used to secure networks. An NIDS is a device or software which monitors all traffic passing a strategic point for malicious activities. When such an activity is detected, an alert is generated. Typically, an NIDS is deployed at a single point, for example, at the Internet gateway. Table 3 summarizes the attacks in the network intrusion detection subdomain.

Clements et al. [30] conducted a white-box inference integrity attack against Kitsune [81], an ensemble of autoencoders for online network intrusion detection. Kitsune uses damped packet statistics which are fed into a feature mapper that divides the features between the autoencoders, to ensure fast online training and prediction. The RMSE output of each autoencoder is fed into another autoencoder that provides the final RMSE score used for anomaly detection. This architecture can be executed on small, weak routers.

Clements et al. used four adversarial methods: FGSM, JSMA, C&W, and ENM (Section 3). The attacker uses the \( L_p \) distance on the feature space between the original input and the perturbed input as the distance metric. Minimizing the \( L_0 \) norm correlates to altering a small number of extracted features. This method has two main limitations: (1) The threat model assumes that the attacker knows the attacked classifier’s features, architecture, and hyperparameters. This makes this attack a white-box attack, rather than a black-box attack. This is a less realistic assumption in real-life scenarios. (2) The modification is made at the feature level (i.e., modifying only the feature vector) and not at the
Table 3. Comparison of Adversarial Learning Approaches in Network Intrusion Detection

| Citation | Year | Attacked Classifier | Attack Type | Attack’s Output | Threat Model | Perturbed Features |
|----------|------|---------------------|-------------|-----------------|--------------|--------------------|
| [30]     | 2019 | Autoencoders        | Inference   | Feature vector  | White-box    | Protocol statistical features |
|          |      | Ensemble            | integrity   |                 |              |                    |
| [74]     | 2018 | SVM, NB, MLP, LR, DT, RF, KNN | Inference integrity | Feature vector | Gray-box    | Statistical and protocol header features |
|          |      |                     |             |                 |              |                    |
| [144]    | 2018 | DNN                 | Inference   | Feature vector  | Gray-box    | Same as [74]        |
|          |      |                     | integrity   |                 |              |                    |
| [98]     | 2017 | DT, RF, SVM         | Inference   | Feature vector  | Gray-box    | Same as [74]        |
|          |      |                     | integrity   |                 |              |                    |
| [136]    | 2018 | MLP                 | Inference   | Feature vector  | White-box    | Same as [74]        |
|          |      |                     | integrity   |                 |              |                    |
| [135]    | 2018 | MLP                 | Inference   | Feature vector  | White-box    | Same as [74]        |
|          |      |                     | integrity   |                 |              |                    |
| [69]     | 2019 | DAGMM, AE, AnoGAN, ALAD, DSVDD, OC-SVM, IF | Inference integrity | PCAP file (end-to-end) | Query-limited gray-box | Similar to [74], but modifies only non-impactful features like send time |
|          |      |                     |             |                 |              |                    |
| [56]     | 2019 | FC DNN, SNN         | Inference   | Feature vector  | Gray-box    | Statistical and protocol header features |
|          |      |                     | integrity   |                 |              |                    |
| [54]     | 2019 | MLP, CNN, LSTM      | Inference   | Feature vector  | White-box    | Features from SDN messages |
|          |      |                     | integrity, training availability |                 |              |                    |

sample level (i.e., modifying the network stream). This means that there is no guarantee that those perturbations can be performed without harming the malicious functionality of the network stream. The fact that some of the features are statistical makes the switch from vector modification to sample modification even more difficult.

Lin et al. [74] generated adversarial examples using a GAN, called IDSGAN, in which the GAN’s discriminator obtains the labels from the black-box attacked classifier. The adversarial examples are evaluated against several attacked classifiers: SVM, Naive Bayes, MLP, logistic regression, decision tree, random forest, and k-nearest neighbors classifiers. This attack assumes knowledge about the attacked classifier’s features, making it a gray-box inference integrity attack. The features include individual TCP connection features (e.g., the protocol type), domain knowledge-based features (e.g., a root shell was obtained), and statistical features of the network sessions (like the percentage of connections that have SYN errors in a time window). All features are extracted from the network stream (the NSL-KDD dataset [127]). This attack generates a statistical feature vector, but the authors don’t explain how to produce a real malicious network stream that has those properties.

Yang et al. [144] trained a DNN model to classify malicious behavior in a network using the same features as [74], achieving performance comparable to state-of-the-art NIDS classifiers; they then showed how to add small perturbations to the original input to lead the model to misclassify malicious network packets as benign while maintaining the
maliciousness of the packets, assuming an adversary without knowledge about the classifier’s architecture is attempting to launch a black-box attack. Three different black-box attacks were attempted by the adversary: an attack based on zeroth-order optimization (ZOO; see Section 3), an attack based on a GAN (similar to the one proposed by [74]), and an attack on which a substitute model is trained and then a C&W attack (see Section 3) is performed against the substitute model. The application of the generated adversarial example against the attacked classifier is successful due to the transferability property (Section 3). This paper has the same limitations as [74]: this gray-box inference integrity attack assumes knowledge about the attacked classifier’s features and also generates only the feature vectors and not the samples themselves.

In their gray-box inference integrity attack, Rigaki and Elragal [98] used the NSL-KDD dataset. Both FGSM and JSMA (Section 3) attacks were used to generate adversarial examples against an MLP substitute classifier, and the results were evaluated against decision tree, random forest, and linear SVM classifiers. This paper has the same limitations as [74]: this attack assumes knowledge about the attacked classifier’s features and also generates only the feature vectors and not the samples themselves.

Warzynskiet et al. [136] performed a white-box inference integrity feature vector attack against an MLP classifier trained on the NSL-KDD dataset. They used a white-box FGSM attack (see Section 3). Wang et al. [135] added three more white-box attacks: JSMA, DeepFool, and C&W (see Section 3). The $L_p$ distance and perturbations are in the feature space in both cases.

Kuppa et al. [69] proposed a query-limited gray-box inference integrity attack against deep unsupervised anomaly detectors, which leverages a manifold approximation algorithm for query reduction and generates adversarial examples using spherical local subspaces while limiting the input distortion and KL divergence. Seven state-of-the-art anomaly detectors with different underlying architectures were evaluated: deep autoencoding Gaussian mixture model, autoencoder, AnoGAN, adversarially learned anomaly detection, deep support vector data description, one-class support vector machines, and isolation forests (see Section 3). All classifiers were trained on the CSE-CIC-IDS2018 dataset and features [112]. Unlike other papers mentioned in this section, the authors generated a full PCAP file (and not just feature vectors) and modified only features that could be modified without harming the network stream (e.g., time-based features), so they actually created adversarial samples and not just feature vectors. However, they did not run the modified stream in order to verify that the malicious functionality indeed remained intact.

Ibitoye et al. [56] attacked a fully connected DNN and a self-normalizing neural network (an SNN is a DNN with a SeLU activation layer; [61]) classifier trained on the BoT-IoT dataset and features [64], using FGSM (see Section 3), the basic iteration method, and the PGD at the feature level. They showed that both classifiers were vulnerable although SNN was more robust to adversarial examples.

Huang et al. [54] attacked port scanning detectors in a software-defined network (SDN). The detectors were MLP, CNN, and LSTM classifiers trained on features extracted from Packet-In messages (used by port scanning tools like Nmap in the SDN) and switch monitoring statistic messages (STATS). The white-box inference integrity attacks used were FGSM and JSMA (see Section 3). The JSMA attack was also (successfully) conducted on regular traffic packets (JSMA reverse) to create false negatives, creating noise and confusion in the network (a white-box training availability attack).
Table 4. Comparison of Adversarial Learning Approaches in Spam Filtering

| Citation | Year | Attacked Classifier | Attack Type | Attack’s Output | Threat Model | Perturbed Features |
|----------|------|---------------------|-------------|-----------------|--------------|--------------------|
| [111]    | 2018 | SVM, kNN, DT, RF    | Inference integrity and confidentiality | Feature vector | Gray-box | Email words or same as [74] |
| [55, 84] | 2011 | Bayesian spam filter | training availability | email (end-to-end) | Gray-box | Email words |
| [17]     | 2014 | SVM and LR          | Inference integrity | email (end-to-end) | White-box | Email words |
| [19]     | 2012 | NB, SVM             | Inference integrity | email (end-to-end) | Gray-box | Email words |
| [68]     | 2018 | NB, LSTM, 1D CNN    | Inference integrity | email (end-to-end) | Gray-box | Email words |
| [71]     | 2018 | LSTM, 1D CNN        | Inference integrity | email (end-to-end) | Gray-box | Email words |
| [83]     | 2017 | LR, MLP             | Training integrity | Feature vector | Gray-box; add and read training set access | Email words |

5.4 Spam Filtering

The purpose of a spam filter is to decide whether an incoming message is legitimate (i.e., ham) or unsolicited (i.e., spam). Spam detectors were among the first applications to use machine learning in the cyber security domain and therefore were the first to be attacked. Table 4 summarizes attacks in the spam filtering subdomain.

Huang et al. [55] attacked SpamBayes [99], which is a content-based statistical spam filter that classifies email using token counts. SpamBayes computes a spam score for each token in the training corpus based on its occurrence in spam and non-spam emails. The filter computes a message’s overall spam score based on the assumption that the token scores are independent, and then it applies Fisher’s method for combining significance tests to determine whether the email’s tokens are sufficiently indicative of one class or the other. The message score is compared against two thresholds to select the label: spam, ham (i.e., non-spam), or unsure.

Huang et al. designed two types of training availability attacks. The first is an indiscriminate dictionary attack, in which the attacker sends attack messages that contain a very large set of tokens—the attack’s dictionary. After training on these attack messages, the victim’s spam filter will have a higher spam score for every token in the dictionary. As a result, future legitimate email is more likely to be marked as spam, since it will contain many tokens from that lexicon. The second attack is a targeted attack—the attacker has some knowledge of a specific legitimate email he/she targets to be incorrectly filtered. Nelson et al. modeled this knowledge by letting the attacker know a certain fraction of tokens from the target email, which are included in the attack message.
Biggio et al. [17] evaluated the robustness of linear SVM and logistic regression classifiers to a white-box inference integrity attack where the attacker adds the most impactful good words and found that while both classifiers have the same accuracy for unperturbed samples, the logistic regression classifier outperforms the SVM classifier in robustness to adversarial examples.

Brückner et al. [19] modeled the interaction between the defender and the attacker in the spam filtering domain as a static game in which both players act simultaneously; i.e., without prior information about their opponent’s move. When the optimization criterion of both players depends not only on their own action but also on their opponent’s move, the concept of a player’s optimal action is no longer well-defined, and thus the cost functions of the learner (the defender) and the data generator (the attacker) are not necessarily antagonistic. They identify the conditions under which this prediction game has a unique Nash equilibrium and derive algorithms that find the equilibrial prediction model. From this equation, they derived new equations for the Nash logistic regression and Nash SVM using custom loss functions. The authors showed that both the attacker and the defender are better off using or attacking the Nash classifiers.

Sethi and Kantardzic [111] trained several classifiers (linear SVM, k-nearest neighbors, SVM with RBF kernel, decision tree, and random forest) on several datasets, including the Spambase dataset for spam detection and KDD99 for network intrusion detection. They presented a query-limited gray-box anchor point inference integrity attack which is effective against all models and a gray-box inference integrity and confidentiality attack which is not query-limited.

Generalized attack methods, which are effective against several NLP classifiers, are a recent trend. Kuleshov et al. [68] implemented such a generalized black-box inference integrity attack to evade NLP classifiers, including spam filtering, fake news detection, and sentiment analysis. The greedy attack finds semantically similar words (enumerating all possibilities to find words with a minimal distance and score difference from the original input) and replacing them in sentences with a high language model score. Three classifiers were evaded: NB, LSTM, and a word-level 1D CNN.

Lei et al. [71] did the same while using a joint sentence and word paraphrasing technique to maintain the original semantics and syntax of the text. They attacked LSTM and a word-level 1D CNN trained on the same datasets used by [68], providing a more effective attack for every dataset, including spam filtering.

This interesting approach of generalization can be extended in the future by applying other NLP-based attacks in the domain of spam adversarial examples.

5.5 Cyber-Physical Systems and Industrial Control Systems

Cyber-physical systems (CPSs) and industrial control systems (ICSs) consist of hardware and software components that control and monitor physical processes, e.g., critical infrastructure, including the electric power grid, transportation networks, water networks, nuclear plants, and autonomous car driving. Table 5 summarizes the attacks in the malware detection subdomain.

Specht et al. [118] trained a fully connected DNN on the SECOM dataset, recorded from a semi-conductor manufacturing process, which consists of 590 attributes collected from sensor signals and variables during manufacturing cycles. Each sensor data entry is labeled as either a normal or anomalous production cycle. They used the FGSM white-box inference integrity feature vector attack to camouflage abnormal/dangerous sensor data as normal.

Ghafouri et al. [40] conducted a gray-box inference integrity attack on a linear regression-based anomaly detector, neural network regression anomaly detector, and an ensemble of both, using the TE-PCS dataset, which contains sensor data describing two simultaneous gas-liquid exothermic reactions for producing two liquid products. There are safety
Table 5. Comparison of Adversarial Learning Approaches in Cyber-Physical Systems

| Citation | Year | Attacked Classifier | Attack Type | Attack’s Output | Threat Model | Perturbed Features |
|----------|------|---------------------|-------------|-----------------|--------------|-------------------|
| [118]    | 2018 | FC DNN              | Inference integrity | Feature vector | White-box Sensor signals |
| [40]     | 2018 | LR, DNN             | Inference integrity | Feature vector | Gray-box Sensor data |
| [29]     | 2018 | RL Q-learning       | Inference integrity | Feature vector | White-box Ultrasonic collision avoidance sensor data |
| [36]     | 2017 | LSTM                | Inference integrity | Feature vector | Gray-box Sensor data |
| [34]     | 2019 | Autoencoders        | Inference integrity/ availability | Feature vector | Gray-box Sensor data |
| [143]    | 2019 | RNN                 | Inference integrity | Feature vector | White-box Continuous sensor data |
| [72]     | 2020 | FC DNN              | Inference integrity | Feature vector | Gray-box Sensor data |

constraints that must not be violated (e.g., safety limits for the pressure and temperature of the reactor), corresponding to the data. For the linear regression-based anomaly detector, the problem of finding adversarial examples of sensor data can be solved using a mixed integer linear programming (MILP) problem. In order to bypass the neural network regression and ensemble, an iterative algorithm is used. It takes small steps in the direction of increasing objective function. In each iteration, the algorithm linearizes all of the neural networks at their operating points and solves the problem using MILP as before.

Clark et al. [29] used a Jaguar autonomous vehicle (JAV) to emulate the operation of an autonomous vehicle. The driving and interaction with the JAV environment used the Q-learning reinforcement learning algorithm. JAV acts as an autonomous delivery vehicle and transports deliveries from an origination point to a destination location. The attacker’s goal is to cause the JAV to deviate from its learned route to an alternate location where it can be ambushed. A white-box inference integrity attack was chosen with the goal of compromising the JAV’s reinforcement learning (RL) policy and causing the deviation. The attack was conducted by inserting an adversarial data feed into the JAV via its ultrasonic collision avoidance sensor.

Feng et al. [36] presented a gray-box inference integrity attack against an LSTM anomaly detector using a GAN (see Appendix A) with a substitute model as a discriminator. Two use cases were evaluated: gas pipeline and water treatment plant sensor data. Li et al. [72] presented a gray-box inference integrity attack against the same dataset but used a constraint-based adversarial machine learning to adhere to the intrinsic constraints of the physical systems, modeled by mathematical constraints derived from normal sensor data.

Erba et al. [34] showed inference integrity and availability attacks against an autoencoder-based anomaly detection of water treatment plant sensor data. Access to both the ICS features and benign sensor data (to train a substitute model) is assumed, making this attack a gray-box attack. This attack enumerates all possible operations for every sensor.
Yaghoubi et al. [143] presented a gray-box inference integrity attack against a steam condenser with an RNN-based anomaly detector of continuous (e.g., signal) data. The attack uses gradient-based local search with either uniform random sampling or simulated annealing optimization to find the data to modify.

5.6 Biometric Systems
In this subsection, we focus on the most commonly used biometric systems that leverage machine learning: face, speech, and iris. Many studies have focused on adversarial attacks against other types of biometric systems, for instance: handwritten signature verification [47], EEG biometrics [85], and gait biometric recognition [93]). However, as previously mentioned, these are not discussed here due to space limitations. Table 6 summarizes the attacks in the malware detection subdomain.

5.6.1 Face Recognition. Sharif et al. [113] presented an inference integrity attack against face recognition systems. The target classifier for the white-box attack was VGG-Face, a 39 layer CNN [90]. The attacked classifier for the black-box attack was the Face++ cloud service. Instead of perturbing arbitrary pixels in the facial image, this attack only perturbed the pixels of eyeglasses which were worn by the attacker, so the attacker could either be classified as another person (label-target attack) or not be classified as him/herself (indiscriminate attack). Both attacks are feature-targeted. Sharif et al. used a Commodity inkjet printer to print the front plane of the eyeglass frames on glossy paper, which the authors then affixed to the actual eyeglass frames when physically performing attacks.

Chen et al. [26] and Liu et al. [78] used a black-box training integrity poisoning attack against face recognition systems. The CNN attacked classifiers were VGG-Face [90] and DeepID [124]. Liu et al. used a non-physical image, such as a square appearing in the picture, as the Trojan trigger in the picture to be labeled as a different person. In [26], the poisoned facial images contained a physical accessory as the key; a photo of a person taken directly from the camera can then become a backdoor when the physical accessory is worn. Thus, this is both a feature-targeted and label-targeted attack. Both attacks require training set add access.

5.6.2 Speaker Verification/Recognition. Note that in this subsection, we only discuss speaker recognition and verification system adversarial attacks.

Kreuk et al. [66] presented white-box inference integrity attacks on an LSTM/GRU classifier that was either trained on the YOHO or NTIMIT datasets using two types of features: Mel-spectrum features and MFCCs. They also presented two black-box inference integrity attacks, using the transferability property. In the first one, they generated adversarial examples with a system trained on NTIMIT and performed the attack on a system that was trained on YOHO. In the second one, they generated the adversarial examples with a system trained using Mel-spectrum features and performed the attack on a system trained using MFCCs. All of the attacks used the FGSM attack, and the attack output was a feature vector and not a complete audio sample.

Gong and Poellabauer [41] trained a WaveRNN model (a mixed CNN-LSTM model) on raw waveforms (the IEMOCAP dataset’s utterances) for speaker recognition, as well as for emotion and gender recognition. They used a substitute waveCNN model and performed a black-box inference integrity attack using FGSM on the raw waveforms, rather than on the acoustic features, making this an end-to-end attack that does not require an audio reconstruction step.

Du et al. [32] used six state-of-the-art speech command recognition CNN models: VGG19, DenseNet, ResNet18, ResNeXt, WideResNet18, and DPN-92, all adapted to the raw waveform input. The models were trained for speaker
| Citation   | Year | Attacked Classifier | Biometric Application | Attack Type | Attack’s Output | Threat Model | Perturbed Features |
|------------|------|---------------------|-----------------------|-------------|-----------------|--------------|-------------------|
| [113]      | 2016 | CNN                 | Face recognition      | Inference   | Physical eyeglasses (end-to-end) | Feature-targeted White-box and Black-box | Image’s pixels    |
| [78]       | 2018 | CNN                 | Face recognition      | Training    | Image (non-physical end-to-end) | Feature-targeted White-box; add training set access | Image’s pixels    |
| [26]       | 2017 | CNN                 | Face recognition      | Training    | Physical accessory (end-to-end) | Feature-targeted White-box; add training set access | Image’s pixels    |
| [66]       | 2018 | LSTM/GRU            | Speaker recognition   | Inference   | Feature vector   | White-box or Black-box | Mel-spectrum features and MFCCs |
| [41]       | 2017 | Mixed CNN-LSTM      | Speaker recognition   | Inference   | Raw waveform (end-to-end) | Black-box | Raw wave-forms   |
| [32]       | 2019 | CNN                 | Speaker recognition   | Inference   | Raw waveform (end-to-end) | Black-box | Raw wave-forms   |
| [20]       | 2018 | CNN                 | Speaker recognition   | Inference   | Feature vector   | Gray-box | Mel-spectrum features |
| [134]      | 2018 | CNN                 | Face recognition, iris recognition | Inference   | Image (non-physical end-to-end) | Gray-box | Image’s pixels |
| [126]      | 2019 | CNN                 | Fingerprint recognition, iris recognition | Inference   | Image (non-physical end-to-end) | White-box | Image’s pixels |
| [116, 117] | 2019 | CNN                 | Iris recognition      | Inference   | Feature vector   | Gray-box | Iris codes       |
recognition on the IEMOCAP dataset and for speech recognition, sound event classification, and music genre classification using different datasets. The black-box inference integrity attack used FGSM or particle swarm optimization (PSO) on the raw waveforms.

Cai et al. [20] trained a CNN classifier that performs multi-speaker classification using Mel-spectrograms as input. They used a Wasserstein GAN with gradient penalty (WGAN-GP) to generate adversarial examples for an indiscriminate gray-box inference integrity attack and also used a WGAN-GP with a modified objective function for a specific speaker for a targeted attack. The attack output is a feature vector of Mel-Spectrograms and not an audio sample.

5.6.3 Iris and Fingerprint Systems. Wang et al. [134] performed an indiscriminate black-box inference integrity attack, leveraging the fact that many image-based models, including face recognition and iris recognition models, use transfer learning, i.e., they add new layers on top of pretrained layers which are trained on a different model (a teacher model, with a known architecture) and are used to extract high-level feature abstractions from the raw pixels. For instance, the face recognition model’s teacher model can be VGG-Face [90], while an iris model’s teacher model is VGG16. By attacking the teacher model using white-box attacks, such as C&W, the target model (student model), for which the architecture is unknown, is also affected.

Taheri et al. [126] trained a CNN classifier on the CASIA dataset of images of iris and fingerprint data. They implemented a white-box inference integrity attack using the FGSM, JSMA, DeepFool, C&W, and PGD methods to generate the perturbed images.

Soleymani et al. [116, 117] generated adversarial examples for code-based iris recognition systems using a gray-box inference integrity attack. However, conventional iris code generation algorithms are not differentiable with respect to the input image. Generating adversarial examples requires backpropagation of the adversarial loss. Therefore, they used a deep autoencoder substitute model to generate iris codes that were similar to iris codes generated by a conventional algorithm (OSIRIS). This substitute model was used to generate the adversarial examples using FGSM, iterative gradient sign method (iGSM), and DeepFool attacks.

6 CURRENT GAPS AND FUTURE RESEARCH DIRECTIONS FOR ADVERSARIAL LEARNING IN THE CYBER SECURITY DOMAIN

In this section, we highlight gaps in our taxonomy, presented in Section 4, which are not covered by the applications presented in Section 5, despite having a required functionality. Each such gap is presented in a separate subsection below. For each gap, we summarize the progress made on this topic in other domains of adversarial learning, such as the computer vision domain, and from this, we extrapolate future trends in the cyber security domain.

6.1 Attack’s Targeting Gap: Feature-Targeted Attacks and Defenses

Poisoning integrity attacks place mislabeled training points in a region of the feature space far from the rest of the training data. The learning algorithm labels such a region as desired, allowing for subsequent misclassifications at test time. However, adding samples to the training set might cause misclassification of many samples and thus would arise suspicion, while the adversary might want to evade a specific sample only (e.g., a dedicated APT).

In non-cyber domains, a feature-targeted attack, also known as a Trojan neural network attack (Liu et al. [78]) or backdoor attack (Gu et al. [46], Chen et al. [26]) is a special form of poisoning attack, which aims to resolve this problem. A model poisoned by a backdoor attack should still perform well on most inputs (including inputs that the end user may
hold out as a validation set) but cause targeted misclassifications or degrade the accuracy of the model for inputs that
satisfy some secret, attacker-chosen property, which is referred to as the backdoor trigger. For instance, adding a small
rectangle to a picture would cause it to be classified with a specific target label [78]. Such attacks were performed on
face recognition [26, 78], traffic sign detection ([46], sentiment analysis, speech recognition, and autonomous driving
[78] datasets.

However, such attacks have not yet been applied in the cyber domain, despite the fact that such attacks have
interesting use cases. For instance, such an attack might allow only a specific nation-state APT to bypass the malware
classifier, while still detecting other malware, leaving the defender unaware of this feature-targeted attack.

Defenses against such attacks are also required. In the image recognition domain, Wang et al. [133] generated a
robust classifier by pruning out backdoor-related neurons from the original DNN. Gao et al. [38] detected a Trojan
attack during runtime by perturbing the input and observed the randomness of predicted classes for perturbed inputs
from a given deployed model. A low entropy in predicted classes implies the presence of a Trojaned input. Once
feature-targeted attacks are published in the cyber security domain, defense methods to mitigate them will likely follow.

6.2 Attacker’s Goals and Knowledge Gap: Confidentiality Attacks via Model Queries and Side
Channels

Reverse engineering (reversing) of traditional (non-ML based) anti-malware is a fundamental part of a malware
developer’s modus operandi. So far, confidentiality attacks have only been conducted against image recognition models
and not against, e.g., malware classifiers. However, performing such attacks in the cyber security domain might provide
the attacker with enough data to perform more effective white-box attacks, instead of black-box ones.

In the image recognition domain, confidentiality attacks have been conducted by querying the target model. Tramer
et al. [129] formed a query-efficient gray-box (the classifier type should be known) score-based attack. The attack
used equation solving to recover the model’s weights from sets of observed sample-confidence score pairs \((x, h(x))\),
retrieved by querying the target model. For instance, a set of \(n\) such pairs is enough to retrieve the \(n\) weights of a
logistic regression classifier using \(n\)-dimensional input vectors. Wang et al. [132] used a similar approach to retrieve the
model’s hyperparameters (e.g., the factor of the regularization term in the loss function equation).

In non-cyber domains, confidentiality attacks have also been conducted via side-channel information. Duddu et
al. [33] used timing attack side channels to obtain neural network architecture information. Batina et al. [14] used
electromagnetic radiation to obtain neural network architecture information from embedded devices. Hua et al. [53]
used both a timing side channel and off-chip memory access attempts during inference to discover on-chip CNN model
architecture.

6.3 Perturbed Features Gap: Exploiting Vulnerabilities in Machine and Deep Learning Frameworks

In non-ML based cyber security solutions, vulnerabilities are commonly used to help attackers reach their goals (e.g., use
buffer overflows to run adversary-crafted code in a vulnerable process). A vulnerability in the underlying application or
operating system is a common attack vector for disabling or bypassing a security product. This trend is starting to be
seen in the adversarial learning domain. However, such attacks are not yet available against malware classifiers and are
only available against image classifiers. Such vulnerabilities are specialized and should be studied explicitly for the
proper cyber use cases in order to be properly exploited in these cases.

In the image recognition domain, Xiao et al. [138] discovered security vulnerabilities in popular deep learning
frameworks (Caffe, TensorFlow, and Torch). Stevens et al. [120] did the same for OpenCV (a computer vision framework),
scikit-learn (a machine learning framework), and in Malheur [97] (a dynamic analysis framework used to classify unknown malware using a clustering algorithm). By exploiting these frameworks’ implementations, attackers can launch denial-of-service attacks that crash or hang a deep learning application, or control-flow hijacking attacks that lead to either system compromise or recognition evasions.

We believe that future adversarial attacks can view the deep learning framework used to train and run the model as a new part of the attack surface, leveraging vulnerabilities in the framework, which can even be detected automatically by a machine learning model (as reviewed in Ghaffarian et al. [39]). Some of those vulnerabilities can be used to add data to input in a way that would cause the input to be misclassified, just as adversarial perturbation would, but by subverting the framework instead of subverting the algorithm. This can be viewed as an extension of the perturbed features attack characteristics in our taxonomy.

6.4 Attack’s Output Gap: End-to-End Attacks in Complex Format Subdomains

As discussed in Section 4.7, only end-to-end attacks can be used to attack systems in the cyber security domain. Some subdomains, such as emails, have a simple format, and therefore it is easier to map from features (words) back to a sample (email) and create an end-to-end attack. However, in more complex subdomains, such as NIDS and CPS, the mapping from features to a full sample (e.g., a network stream) is complex. As can be seen in Sections 5.3 and 5.5, only a small number of attacks in the NIDS and CPS subdomains (less than 10%) are end-to-end attacks.

We predict that like in the computer vision domain, where, after several years of feature vector attacks (e.g., [43]), end-to-end attacks followed [35], the trend in the cyber security domain will be similar. Pierazzi et al. [92] formalized initial theoretical constraints for end-to-end attacks. End-to-end attacks may follow three directions: 1) Adding new features to an existing sample, e.g., [73, 92, 104, 119]. 2) Modifying only a subset of features that can be modified without harming the functionality of an existing sample, e.g., [69, 101]. 3) Using cross-sample transformations (e.g., packing) that would change many features simultaneously [6, 101].

6.5 Adversarial Defense Method Gaps

Our taxonomy is focused in the attack side, but every attack is accompanied by a corresponding defense method. The lack of defense methods against adversarial attacks in the cyber security domain is acute, because this domain involves actual adversaries: malware developers who want to evade next generation machine and deep learning-based classifiers. Such attacks have already been executed in the wild against static analysis deep neural networks [1]. We mapped three different gaps specific to the cyber security domain, which are described below.

6.5.1 Metrics to Measure the Robustness of Classifiers to Adversarial Examples. Several papers ([59, 91, 137]) suggested measuring the robustness of machine learning systems to adversarial attacks by approximating the lower bound on the perturbation needed for any adversarial attack to succeed; the larger the perturbation, the more robust the classifier. However, these papers assume that the robustness to adversarial attacks can be evaluated by the minimal perturbation required to modify the classifier’s decision. This raises the question of whether this metric is valid in the cyber security domain.

Section 2.3 leads us to the conclusion that minimal perturbation is not necessarily the right approach for adversarial learning in the cyber security domain. As already mentioned in Biggio et al. [18], maximum confidence attacks, such as the Carlini and Wagner (C&W) attack (Section 3), are more effective. However, this is not the complete picture.
As mentioned in Section 2.2, in the cyber security domain classifiers usually use more than a single feature type as input (e.g., both PE header metadata and byte entropy in Saxe et al. [106]). Certain feature types are easier to modify without harming the executable’s functionality than others. On the other hand, an attacker can add as many strings as needed; in contrast to images, adding more strings (i.e., a larger perturbation) is not more visible to the user than adding less strings, since the executable file is still a binary file.

This means that we should not only take into account the impact of a feature on the prediction, but also the difficulty of modifying the feature type. Unfortunately, there is currently no numeric metric to assess the difficulty of modifying features. Currently, we must rely on the subjective opinion of experts who assess the difficulty of modifying each feature type, as shown in Katzir and Elovici [60]. When such a metric becomes available, combining it with the maximum impact metric would be a better optimization constraint than minimal perturbation.

In conclusion, both from an adversary’s perspective (when trying to decide which attack to use) and from the defender’s perspective (when trying to decide which classifier would be the most robust to adversarial attack), the metric of evaluation currently remains an open question in the cyber security domain.

6.5.2 Perturbed Features Gap: Defense Methods Designed for the Cyber Security Domain. If adversarial attacks are equivalent to malware attacking a computer (machine learning model), then defense methods can be viewed as an anti-malware product. However, most defense methods have been evaluated in the image recognition domain for CNNs and in the NLP domain for RNNs. Due to space limitations, we cannot provide a complete list of the state-of-the-art prior work in those domains. A more comprehensive list can be found, e.g., in Qiu et al. [94].

Several papers presenting attacks in the cyber security domain (e.g., [45, 115]) have sections showing that the attack is effective even in the presence of well-known defense methods that were evaluated and found effective in the computer vision domain (e.g., distillation and adversarial retraining). However, only a few defense methods were developed specifically for the cyber security domain and its unique challenges, like those described in Section 2. Furthermore, cyber security classifiers usually have a different architecture than computer vision classifiers, against which most published defenses are evaluated.

Chen et al. [25] suggested a method to make an Android malware classifier robust to poisoning attacks. Their method has two phases: an offline training phase that selects and extracts features from the training set and an online detection phase that utilizes the classifier trained by the first phase. These two phases are intertwined through a self-adaptive learning scheme, wherein an automated camouflage detector is introduced to filter the suspicious false negatives and feed them back into the training phase. Stokes et al. [121] evaluated three defense methods: weight decay, an ensemble of classifiers, and distillation for a dynamic analysis malware classifier based on a non-sequence based deep neural network. Rosenberg et al. [103] tried to defend an API call-based RNN classifier and compared their own RNN defense method, sequence squeezing, to five other defense methods inspired by existing CNN-based defense methods: adversarial retraining, statistical anomalous subsequences, defense GAN, nearest neighbor classification, and RNN ensembles. They showed that sequence squeezing provides the best trade-off between training and inference overhead (which is less critical in the computer vision domain) and the adversarial robustness.

Specht et al. [118] suggested an iterative adversarial retraining process to mitigate adversarial examples for semiconductor anomaly detection of sensor data. Soleymani et al. [116] used wavelet domain denoising of the iris samples by investigating each wavelet sub-band and removing the sub-bands that are most affected by the adversary.

Kravchic and Shabtai [65] suggested detecting anomalies and cyber attacks in ICS data using 1D CNNs and under-complete autoencoders (UAEs).
Ghafouri et al. [40] presented robust linear regression and neural network regression-based anomaly detectors for CPS anomalous data detection by modeling a game between the defender and attacker as a Stackelberg game in which the defender first commits to a collection of thresholds for the anomaly detectors, and the attacker then computes an optimal attack. The defender aims to minimize the impact of attacks, subject to a constraint, typically set to achieve a target number of false alarms without consideration of attacks.

Taheri et al. [126] presented an architecture that includes shallow and deep neural networks to defend against biometric adversarial examples. The shallow neural network is responsible for data preprocessing and generating adversarial samples. The deep neural network is responsible for understanding data and information, as well as detecting adversarial samples. The deep neural network gets its weights from transfer learning, adversarial training, and noise training.

In our opinion, additional defense methods proposed for the image recognition domain could inspire similar defense methods in the cyber domain. Furthermore, in this domain further emphasis should be put on the defense method overhead (as done, e.g., in [103]), due to the fact that malware classifiers perform their classification in real time, so unlike in the image recognition domain, low overhead is critical.

6.5.3 Attacker’s Knowledge Gap: Defense Methods Robust to Unknown and Transparent-Box Adversarial Attacks. There are two main challenges when developing a defense method:

The first challenge is creating a defense method which is also robust against transparent-box attacks, i.e., attackers who know what defense methods are being used and select their attack methods accordingly.

In the computer vision domain, [21, 128] showed that many different types of commonly used defense methods (e.g., detection of adversarial examples using statistical irregularities) are rendered useless by a specific type of adversarial attack. He et al. [49] showed the same for feature squeezing, and [10, 48, 57] presented similar results against Defense-GAN.

Similar research should be conducted in the cyber security domain. For instance, attackers can make their attack more robust against RNN subsequence model ensembles presented in [103] by adding perturbations across the entire API call sequence and not just until the classification changes.

The second challenge is creating defense methods that are effective against all attacks and not just specific ones, termed attack-agnostic defense methods in [103]. However, the challenge of finding a metric to evaluate the robustness of classifiers to adversarial attacks in the cyber security domain, discussed in Section 6.5.1, makes the implementation of attack-agnostic defense methods in the cyber security domain more challenging than in other domains.

7 CONCLUSIONS

In this paper, we reviewed the latest research in a wide range of adversarial learning applications in the cyber security domain (e.g., malware detection, network intrusion detection, etc.).

One conclusion is that while feature vector adversarial attacks in the cyber security domain are possible, real-life attacks (e.g., against next generation anti-virus software) are challenging. This is due to the unique challenges that attackers and defenders are faced with in the cyber security domain: the difficulty of modifying samples end-to-end without damaging the malicious business logic, the need to modify many feature types with various levels of modification difficulty, etc.

From the gaps we highlighted in our taxonomy and the recent advancements in other domains of adversarial learning, we identified some of the directions of future research in adversarial learning in the cyber security domain. One of
these directions is the implementation of feature-triggered attacks that would work only if a certain trigger exists, leaving the system’s integrity unharmed in other cases, thus making it harder to detect the attack. Another possible direction is performing confidentiality attacks involving model reversing via queries or side channels. A third direction is expanding the attack surface of adversarial attacks to include the vulnerabilities in the relevant machine learning framework and designing machine learning models to detect and leverage them. From the defender’s point of view, more robust defense methods against adversarial attacks in the cyber security domain would be the focus of future research.

A final conclusion is that adversarial learning in the cyber security domain becomes more and more similar to the cat and mouse game conducted in the traditional cyber security domain, in which attackers implement increasingly sophisticated attacks to evade the defenders and vice versa. A key takeaway is that defenders should become more proactive in assessing their system’s robustness to adversarial attacks, the same way penetration testing is used in the traditional cyber security domain.

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APPENDIX A: DEEP LEARNING CLASSIFIERS: MATHEMATICAL AND TECHNICAL BACKGROUND

Deep Neural Networks (DNNs)

Neural networks are a class of machine learning models made up of layers of neurons (elementary computing units).

A neuron takes an n-dimensional feature vector \( x = [x_1, x_2,...,x_n] \) from the input or a lower level neuron and outputs a numerical output \( y = [y_1, y_2,...,y_m] \), such that

\[
y_j = \phi(\sum_{i=1}^{n} w_{ji}x_i + b_j)
\]

(15)

to the neurons in higher layers or the output layer. For the neuron \( j \), \( y_j \) is the output and \( b_j \) is the bias term, while \( w_{ji} \) are the elements of a layer’s weight matrix. The function \( \phi \) is the nonlinear activation function, such as \( \text{sigmoid}() \), which determines the neuron’s output. The activation function introduces nonlinearities to the neural network model. Otherwise, the network remains a linear transformation of its input signals. Some of the success of DNNs is attributed to these multi-layers of nonlinear correlations between features, which aren’t available in popular traditional machine learning classifiers, such as SVM, which has at most a single nonlinear layer using the kernel trick.

A group of \( m \) neurons forms a hidden layer which outputs a feature vector \( y \). Each hidden layer takes the previous layer’s output vector as the input feature vector and calculates a new feature vector for the layer above it:

\[
y_{l} = \phi(W_{l}y_{l-1} + b_{l})
\]

(16)

where \( y_{l}, W_{l} \) and \( b_{l} \) are the output feature vector, weight matrix, and bias of the \( l \)-th layer, respectively. Proceeding from the input layer, each subsequent higher hidden layer automatically learns a more complex and abstract feature representation which captures a higher level structure.

Convolutional Neural Networks (CNNs). CNNs are a type of DNN. Let \( x_{i} \) be the k-dimensional vector corresponding to the \( i \)-th element in the sequence. A sequence of length \( n \) (padded when necessary) is represented as: \( x[0:n-1] = x[0] \perp x[1] \perp ... \perp x[n-1] \), where \( \perp \) is the concatenation operator. In general, let \( x[i:i+j] \) refer to the concatenation of words \( x[i], x[i+1], ... , x[i+j] \). A convolution operation involves a filter \( w \), which is applied to a window of \( h \) elements to produce a new feature. For example, a feature \( c_{i} \) is generated from a window of words \( x[i:i+h-1] \) by:

\[
c_{i} = \phi(W_{x}x[i:i+h] + b)
\]

(17)

where \( b \) is the bias term and \( \phi \) is the activation function. This filter is applied to each possible window of elements in the sequence \( x[0:h-1], x[1:h], ... , x[n-h:n-1] \) to produce a feature map: \( c = [c_0, c_1, ..., c_{n-h}] \). We then apply a max-over-time pooling operation over the feature map and take the maximum value: \( \hat{c} = \max(c) \) as the feature corresponding to this particular filter. The idea is to capture the most important feature (the one with the highest value) for each feature map.

We described the process by which one feature is extracted from the filter above. The CNN model uses multiple filters (with varying window sizes) to obtain multiple features. These features form the penultimate layer and are passed to a fully connected softmax layer whose output is the probability distribution over labels.

CNNs have two main differences from fully connected DNNs:

(1) CNNs exploit spatial locality by enforcing a local connectivity pattern between neurons of adjacent layers. The architecture thus ensures that the learned “filters” produce the strongest response to a spatially local input pattern. Stacking many such layers leads to nonlinear “filters” that become increasingly “global.” This allows the
network to first create representations of small parts of the input and assemble representations of larger areas from them.

(2) In CNNs, each filter is replicated across the entire input. These replicated units share the same parameterization (weight, vector, and bias) and form a feature map. This means that all of the neurons in a given convolutional layer respond to the same feature (within their specific response field). Replicating units in this way allows for features to be detected regardless of their position in the input, thus constituting the property of translation invariance. This property is important in both image problems and with sequence input, such as API call traces.

**Recurrent Neural Networks (RNNs)**

A limitation of neural networks is that they accept a fixed sized vector as input (e.g., an image) and produce a fixed sized vector as output (e.g., probabilities of different classes). Recurrent neural networks can use sequences of vectors in the input, output, or both. In order to do that, the RNN has a hidden state vector, the context of the sequence, which is combined with the current input to generate the RNN’s output.

Given an input sequence \([x_1, x_2, \ldots, x_T]\), the RNN computes the hidden vector sequence \([h_1, h_2, \ldots, h_T]\) and the output vector sequence \([y_1, y_2, \ldots, y_T]\) by iterating the following equations from \(t = 1\) to \(T\):

\[
\begin{align*}
h_t &= \phi(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \\
y_t &= W_{hy}h_t + b_o
\end{align*}
\]

where the \(W\) terms denote weight matrices (e.g., \(W_{xh}\) is the input hidden weight matrix), the \(b\) terms denote bias vectors (e.g., \(b_h\) is the hidden bias vector), and \(\phi\) is usually an element-wise application of an activation function. DNNs without a hidden state, as specified in Equation 18, reduce Equation 19 to the private case of Equation 16, known as feedforward networks.

**Long Short-Term Memory (LSTM).** Standard RNNs suffer from both exploding and vanishing gradients. Both problems are caused by the RNNs’ iterative nature, in which the gradient is essentially equal to the recurrent weight matrix raised to a high power. These iterated matrix powers cause the gradient to grow or shrink at a rate that is exponential in terms of the number of timesteps \(T\). The vanishing gradient problem does not necessarily cause the gradient to be small; the gradient’s components in directions that correspond to long-term dependencies might be small, while the gradient’s components in directions that correspond to short-term dependencies is large. As a result, RNNs can easily learn the short-term but not the long-term dependencies. For instance, a conventional RNN might have problems predicting the last word in: “I grew up in France...I speak fluent French” if the gap between the sentences is large.

The LSTM architecture ([50]), which uses purpose-built memory cells to store information, is better at finding and exploiting long-range context than conventional RNNs. The LSTM’s main idea is that instead of computing \(h_t\) from \(h_{t-1}\) directly with a matrix-vector product followed by a nonlinear transformation (Equation 18), the LSTM directly computes \(\Delta h_t\), which is then added to \(h_{t-1}\) to obtain \(h_t\). This implies that the gradient of the long-term dependencies cannot vanish.

**Gated Recurrent Unit (GRU).** Introduced in [27], the gated recurrent unit (GRU) is an architecture that is similar to LSTM but reduces the gating signals from three (in the LSTM model: input, forget, and output) to two. The two gates
are referred to as an update gate and a reset gate. Some research has shown that a GRU RNN is comparable to, or even outperforms, an LSTM model in many cases, while requiring less training time.

**Bidirectional Recurrent Neural Networks (BRNNs).** One shortcoming of conventional RNNs is that they can only make use of prior context. It is often the case that for malware events the most informative part of a sequence occurs at the beginning of the sequence and may be forgotten by standard recurrent models. Bidirectional RNNs ([110]) overcome this issue by processing the data in both directions with two separate hidden layers, which are then fed forward to the same output layer. A BRNN computes the forward hidden sequence $h_t^→$, the backward hidden sequence $h_t^←$, and the output sequence $y_t$ by iterating the backward layer from $t = T$ to 1 and the forward layer from $t = 1$ to $T$, and subsequently updating the output layer. Combining BRNNs with LSTM results in bidirectional LSTM ([44]), which can access the long-range context in both input directions.

**Generative Adversarial Networks (GANs)**
A GAN is a combination of two deep neural networks: a classification network (the discriminator) which classifies between real and fake inputs and a generative network (the generator) that tries to generate fake inputs that would be misclassified as genuine by the discriminator [42], eventually reaching a Nash equilibrium. The end result is a discriminator which is more robust against fake inputs.

GANs are only defined for real-valued data, while RNN classifiers use discrete symbols. The discrete outputs from the generative model make it difficult to pass the gradient update from the discriminative model to the generative model. Modeling the data generator as a stochastic policy in reinforcement learning can bypass the generator differentiation problem [145].

**Autoencoders (AEs)**
Autoencoders are widely used for unsupervised learning tasks such as learning deep representations or dimensionality reduction. Typically, a traditional deep autoencoder consists of two components, the encoder and the decoder. Let us denote the encoder’s function as $f_θ : X → H$ and denote the decoder’s function as $g_ω : H → X$, where $θ, ω$ are parameter sets for each function, $X$ represents the data space, and $H$ represents the feature (latent) space. The reconstruction loss is:

$$L(θ, ω) = \frac{1}{N} ||X - g_ω(f_θ(X))||^2$$  \((20)\)

where $L(θ, ω)$ represents the loss function for the reconstruction.

**Deep Autoencoding Gaussian Mixture Model (DAGMM)**
The DAGMM [147] uses two different networks, a deep autoencoder and a Gaussian mixture model (GMM) based estimator network, to determine whether a sample is anomalous or not.

**AnoGAN**
AnoGAN [108] is a GAN-based method for anomaly detection. This method involves training a DCGAN [95] and using it to recover a latent representation for each test data sample at inference time. The anomaly score is a combination of reconstruction and discrimination components.
Adversarially Learned Anomaly Detection (ALAD)
ALAD [146] is based on a bidirectional GAN anomaly detector, which uses reconstruction errors from adversarially learned features to determine if a data sample is anomalous. ALAD employs spectral normalization and additional discriminators to improve the encoder and stabilize GAN training.

Deep Support Vector Data Description (DSVDD)
DSVDD [105] trains a deep neural network while optimizing a data-enclosing hypersphere in the output space.

One-Class Support Vector Machine (OC-SVM)
The OC-SVM [109] is a kernel-based method that learns a decision boundary around normal examples.

Isolation Forest (IF)
An isolation forest [75] is a partition-based method which isolates anomalies by building trees using randomly selected split values.