Adversarial Examples for Deep-Learning Cyber Security Analytics

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Abstract—As advances in Deep Neural Networks (DNNs) demonstrate unprecedented levels of performance in many critical domains, their vulnerability to attacks is still an open question. Adversarial examples are small modifications of legitimate data points, resulting in mis-classification at testing time. As DNNs found a wide range of applications to cyber security analytics, it becomes important to study the robustness of these models in this setting.

We consider adversarial testing-time attacks against Deep Learning models designed for cyber security applications. In security applications, machine learning models are not typically trained directly on the raw network traffic or security logs, but on intermediate features defined by domain experts. Existing attacks applied directly to the intermediate feature representation result in violation of feature constraints, leading to invalid adversarial examples. We propose a general framework for crafting adversarial attacks that takes into consideration the mathematical dependencies between intermediate features in model input vector, as well as physical constraints imposed by the applications. We apply our methods on two security applications, a malicious connection and a malicious domain classifier, to generate feasible adversarial examples in these domains. We show that with minimal effort (e.g., generating 12 network connections), an attacker can change the prediction of a model from Malicious to Benign. We extensively evaluate the success of our attacks, and how they depend on several optimization objectives and imbalance ratios in the training data.

I. INTRODUCTION

Deep learning has reached super-human performance in machine learning (ML) tasks for classification in diverse domains, including image classification, speech recognition, and natural language processing. Still, deep neural networks (DNNs) are not robust in face of adversarial attacks, and their vulnerability has been demonstrated extensively in many applications, with the majority of work in adversarial ML being performed in image classification tasks (e.g., [4], [9], [12], [24], [36], [41], [45], [55]).

ML started to be used more extensively in cyber security applications in academia and industry, with the emergence of a new field called security analytics. Among the most popular applications of ML in cyber security we highlight malware classification [5], [8], [47], malicious domain detection [3], [6], [11], [40], [43], and botnet detection [27], [56]. In most of these applications, the raw security datasets (network traffic or host logs) are not used directly as input to the DNN, but instead an intermediate feature extraction layer is defined by domain experts to generate inputs for neural networks (or other ML models). There are efforts to automate the feature engineering aspect (e.g., [32], but it is not yet a common practice. One of the challenges of adapting ML to work in these domains is the large class imbalance during training [6]. Therefore, adversarial attacks designed on continuous domains (for instance, in image classification) need to be adapted to take into account the specifics of cyber security applications.

Initial efforts to design adversarial attacks at testing time (called evasion attacks) for discrete domains are underway in the research community. Examples include PDF malware detection [53], [57] and malware classification [26], [54], but these applications use binary features. Recently, Kulynych et al. [35] introduce a graphical framework for general evasion attacks in discrete domains, that constructs a graph of all possible transformations of an input and selects a set of minimum cost to generate an adversarial example. The previous work, however, cannot yet handle evasion attacks in security applications that respect complex feature dependencies, as well as physical-world constraints.

In this paper we introduce a novel framework for crafting adversarial attacks in cyber security domain that respects the mathematical dependencies given by common operations applied in feature space and enforces at the same time the physical-world constraints of specific applications. At the core of our framework is an iterative optimization method that determines the feature of maximum gradient of attacker’s objective at each iteration, identifies the family of features dependent on that feature, and modifies consistently all the features in the family, while preserving an upper bound on the maximum distance and respecting the physical-world application constraints.

Our general framework has the advantage of being applicable to existing security applications to test their robustness. There is a minimum amount of adaptation that is required for a new application, but most of the building blocks are reusable across applications. To demonstrate this, we apply our framework to two distinct applications. The first is a malicious network traffic classifier for botnet detection (using a public dataset [22]), in which an attacker can insert network connections on ports of his choice that respect the physical network constraints (e.g., TCP and UDP packet sizes) and a number of mathematical dependencies. The second application is malicious domain classification using features extracted from web proxy logs (collected from a large enterprise) that involves a number of statistical and mathematical dependencies in feature space. We demonstrate that the attacks are successful
in both applications, with minimum amount of perturbation. For instance, by inserting 12 network connections an attacker can change the classification prediction from Malicious to Benign in the first application. We perform detailed evaluation to test: (1) if our attacks perform better than several baselines; (2) if the selection of the optimization objective impacts the attack success rate; (3) how the imbalance ratio between the Malicious and Benign classes in training changes the success of the attack; (4) if features modified by the attack are the features with highest importance.

To summarize, our contributions are:
1) We introduce a general evasion attack framework for cyber security that respects mathematical feature dependencies and physical-world constraints.
2) We apply our framework with minimal adaptation to two distinct applications: malicious network connection classifier, and malicious domain detector, to generate feasible adversarial examples in these domains.
3) We demonstrate that our methods perform better than several baselines at creating adversarial examples with smaller distance to the original data points.
4) We extensively evaluate our proposed framework for these applications and quantify the amount of effort required by the attacker to bypass the classifiers, for different optimization objectives and training data imbalance ratios.

Organization. We provide background material on DNNs and evasion attacks in Section II. We discuss the challenges for designing adversarial attacks in cyber security and introduce our general framework in Section III. We instantiate our framework for the two applications of interest in Section IV. We work for the two applications in Sections V and VI, respectively. Finally, we discuss related work in Section VII and conclude in Section VIII.

II. BACKGROUND
A. Deep Neural Networks for Classification

A feed-forward neural network (FFNN) for binary classification is a function \( y = F(x) \) from input \( x \in \mathbb{R}^d \) (of dimension \( d \)) to output \( y \in \{0, 1\} \). The parameter vector of the function (usually denoted \( \theta \)) is learned during the training phase using back propagation over the network layers. Each layer includes a matrix multiplication and non-linear activation (e.g., ReLU). The last layer’s activation is sigmoid \( \sigma \) for binary classification: \( y = F(x) = \sigma(Z(x)) \), where \( Z(x) \) are the logits, i.e., the output of the the penultimate layer. We denote by \( C(x) \) the predicted class for \( x \). For multi-class classification, the last layer uses a softmax activation function with as many neurons as the number of classes. Convolutional neural networks (CNNs) use similar architectures and operations, with the requirement of including a convolution operation in at least one layer.

B. Threat Model

Adversarial attacks against machine learning algorithms can be developed in either the training or testing phase. In this work, we consider testing-time attacks, called evasion attacks. The DNN model is trained correctly and the attacker’s goal is to create adversarial examples at testing time. In security settings, typically the attacker starts with Malicious points that he aims to minimally modify into adversarial examples classified as Benign. We only consider here the modification of Malicious to Benign prediction, but not the reverse (Benign to Malicious), since that is a denial-of-service attack we do not consider here.

We assume the strongest attack model, the white-box attack, in which the attacker has full knowledge of the ML system. White-box attacks have been considered extensively in previous work, e.g., [9], [12], [24], [41] to evaluate the robustness of existing ML classification algorithms. We follow a similar trend and consider white-box evasion attacks to analyze the robustness of DNNs in cyber security under worst-case conditions. In the future, we plan to analyze weaker and more practical adversarial models, including black-box attacks with minimal knowledge of the ML system (such as [44]).

C. Evasion Attacks against Deep Neural Networks

We describe several evasion attacks against DNNs: projected gradient descent-based attacks and the penalty-based attack of Carlini and Wagner.

Projected gradient attacks. This is a class of attacks based on gradient descent for objective minimization, that project the adversarial points to the feasible domain at each iteration. For instance, Biggio et al. [9] use an objective that maximizes the confidence of adversarial examples, within a ball of fixed radius in \( L_1 \) norm. Madry et al. [41] use the loss function directly as the optimization objective and use the \( L_2 \) and \( L_\infty \) distances for projection.

C&W attack. Carlini and Wagner [12] solve the following optimization problem to create adversarial example against CNNs used for multi-class prediction:

\[
\delta = \arg \min ||\delta||_2 + c \cdot h(x + \delta)
\]

\[
h(x + \delta) = \max(0, \max(Z_k(x + \delta) : k \neq t) - Z_t(x + \delta)),
\]

where \( Z() \) are the logits of the DNN.

This is called the penalty method, and the optimization objective has two terms: the norm of the perturbation \( \delta \), and a function \( h(x + \delta) \) that is minimized when the adversarial example \( x + \delta \) is classified as the target class \( t \). This two objectives are balanced by constant \( c \), determined by performing a grid search. The attack works for \( L_0 \), \( L_2 \), and \( L_\infty \) norms.

III. METHODOLOGY

In this section, we start by describing the classification setting in cyber security analytics. Then we devote the majority of the section to describe evasion attacks for cyber security, mention challenges of designing them, and presenting our new attack framework that takes into consideration the specific constraints of security applications.
A. Machine learning classification in cyber security

In standard computer vision tasks such as image classification, the raw data (image pixels) is used directly as input into the neural network models. The promise of deep learning is end-to-end learning, including learning feature representations from the raw data. Deep learning is extremely successful at achieving this for image, text, and speech applications. In contrast, in cyber security, domain expertise is still required to generate intermediate features from the raw data (e.g., network traffic or endpoint data) (see Figure 1).

Machine learning is commonly used in cyber security for classification of Malicious and Benign activity (see for example previous work in this space [11], [40], [43]). A raw dataset $R$ is initially collected (for example, pcap files or Netflow logs), and feature extraction is performed by applying different operators, such as $\text{Max}$, $\text{Min}$, $\text{Avg}$, and $\text{Total}$. The training dataset $D_{tr}$ has $N$ training examples: $D_{tr} = \{(x^{(1)}, L^{(1)}), \ldots, (x^{(N)}, L^{(N)})\}$, each example $x^{(i)}$ being a $d$-dimensional feature vector: $x^{(i)} = (x^{(i)}_1, \ldots, x^{(i)}_d)$. Features of the training dataset are most of the time obtained by application of some operator or function $O_p$ on the raw data $x^{(i)} = O_p(R)$. The set of all supported operators or functions applied to the raw data is denoted by $O$. A data point $x = (x_1, \ldots, x_d)$ in feature space is feasible if there exists some raw data $r$ such as for all $j$, there exists a operator $O_{p_j} \in O$ with $x_j = O_{p_j}(r)$. The set of all feasible points for raw data $R$ and operators $O$ are called feasible Set($R, O$).

An example of feasible and unfeasible points is illustrated in Table 1.

![Table 1: Example of feasible and unfeasible features.](image)

### C. Overview of our approach

To address these issues, we introduce a framework for evasion attacks that preserves a range of feature dependencies and guarantees that the produced adversarial examples are within the feasible region of the domain. Our framework supports two main types of constraints:

- **Mathematical feature dependencies**: These are dependencies created in the feature extraction layer. For instance, by applying several mathematical operators ($\text{Max}$, $\text{Min}$, $\text{Total}$) over a set of raw log data, we introduce feature dependencies. See the example in Figure 2 for Bro connection log events and several dependent features constructed using these operators. For instance, a Bro connection includes the number of packets sent and received, and we define the $\text{Min}$, $\text{Max}$, and $\text{Total}$ number of packets sent and received by the same source IP on a particular port (within a fixed time window). We use the terminology *family of features* to denote a subset of features that are inter-connected and need to be updated simultaneously. For the Bro example, the features defined for each port (e.g., 80, 53, 22) are dependent as they are generated from all the connections on that port.
- **Physical-world constraints**: These are constraints imposed by the real-world application. For instance, in the case of network traffic, a TCP packet has a maximum size of 1500 bytes.

Our starting point for the attack framework are gradient-based optimization algorithms, including projected [9], [41] and penalty-based [12]. Of course, we cannot apply these attacks directly since they will not preserve the feature dependencies. To overcome this, we use the values of the objective gradient at each iteration to select features of maximum gradient values. We create feature-update algorithms for each
family of dependencies that use a combination of gradient-based method and mathematical constraints to always maintain a feasible point that satisfies the constraints. We also use various projection operators to project the updated adversarial examples to feasible regions of the feature space.

D. Proposed Evasion Attack Framework

We introduce here our general evasion attack framework for creating adversarial examples at testing time for binary classifiers. In the context of security applications, the main goal of the attacker is to ensure that a Malicious data point is classified as Benign after applying a minimum amount of perturbation to it. We consider binary classifiers designed using FFNN architectures and the strongest adversarial model, i.e., a white-box attack with knowledge of the ML process. For measuring the amount of perturbation added by the original example, we use the $L_2$ norm.

Algorithm 1 describes the general framework. The input consists of: an input sample $x$ with label $y$ (typically Malicious in security applications); a target label $t$ (typically Benign); the model prediction function $C$; the optimization objective $G$; maximum allowed perturbation $d_{max}$; the subset of features $F_S$ that can be modified; the features that have dependencies $F_D \subset F_S$; the maximum number of iterations $M$ and a learning rate $\alpha$ for gradient descent. The set of features with dependencies are split into families of features. A family is defined as a subset of $F_D$ such that features within the family need to be updated simultaneously, whereas features outside the family can be updated independently.

The algorithm proceeds iteratively. The goal is to update the data point in the direction of the gradient (to minimize the optimization objective), while preserving the family dependencies, as well as the physical-world constraints. In each iteration, the gradients of all modifiable features are computed, and the feature of maximum gradient is selected. The update of the data point $x$ in the direction of the gradient is performed as follows:

1. If the feature of maximum gradient belongs to a family with other dependent features, function UPDATE_FAMILY is called (line 10). Inside the function, the representative feature for the family is computed (this needs to be defined for each application). The representative feature is updated first, according to its gradient value, followed by updates to other dependent features using function UPDATE_DEP (line 32). We need to define the function UPDATE_DEP for each application, but we use a set of building blocks that are reusable. Once all features in the family have been updated, there is a possibility that the update data point exceeds the allowed distance threshold from the original point. If that is the case, the algorithm backtracks and performs a binary search for the amount of perturbation added to the representative feature (until it finds a value for which the modified data point is inside the allowed region).

2. If the feature of maximum gradient does not belong to any feature family, then it can be updated independently from other features. The feature is updated using the standard gradient update rule (line 13). This is followed by a projection $\Pi_2$ within the feasible ball in $L_2$ norm.

We currently support two optimization objectives:

**Objective for Projected attack.** We set the objective $G(x) = Z_1(x)$, where $Z_1$ is the logit for the Malicious class, and $Z_0 = 1 - Z_1$ for the Benign class:

$$\delta = \arg \min Z_1(x + \delta),$$

s.t. $||\delta||_2 \leq d_{max}$,

$$x + \delta \in \text{Feasible Set}(R, O)$$

We need to ensure that the adversarial example is in the feasible set to respect the mathematical and physical constraints. **Objective for Penalty attack.** The penalty objective for binary classification is equivalent to:

$$\delta = \arg \min ||\delta||_2 + c \cdot \max(0, Z_1(x + \delta)),$$

$$x + \delta \in \text{Feasible Set}(R, O)$$

![Image of neural network training for image classification (left) and for cyber security analytics (right).](image-url)
Algorithm 1 Framework for Evasion Attack with Constraints

Require: $x$, $y$: the input sample and its label; $t$: target label;
$C$: prediction function; $G$: optimization objective;
$d_{\text{max}}$: maximum allowed perturbation;
$F_S$: subset of features that can be modified
$F_D$: features in $F_S$ that have dependencies;
$M$: maximum number of iterations; $\alpha$: learning rate.

Ensure: $x^*$: adversarial example or $\perp$ if not successful.
1: Initialize $m \leftarrow 0$; $x^0 \leftarrow x$
2: // Iterate until successful or stopping condition
3: while $C(x^m) \neq t$ and $m < M$ do
4:   $\nabla \leftarrow [\nabla G_x(x^m)]_i$ // Gradient vector
5:   $\nabla_S \leftarrow \nabla_{F_S}$ // Gradients of features in $F_S$
6:   $i_{\text{max}} \leftarrow \arg \max_S \nabla_S$ // Feature of max gradient in $F_S$
7:   // Check if feature has dependencies
8:   if $i_{\text{max}} \in F_D$ then
9:     // Update dependent features with constraints
10:    $x^{m+1} \leftarrow \text{UPDATE\_FAMILY}(m, x^m, \nabla, i_{\text{max}})$
11:   else
12:     // Gradient update and project to feasible region
13:     $x^{m+1} \leftarrow x^m_{i_{\text{max}}} - \alpha \nabla_{i_{\text{max}}}$
14:     $\Pi(x^{m+1})$
15:     $F_S \leftarrow F_S \setminus \{i_{\text{max}}\}$
16:     $m \leftarrow m + 1$
17:     if $C(x^m) = t$ then
18:         return $x^* \leftarrow x^m$
19:     else
20:         return $\perp$
21: function UPDATE\_FAMILY($m, x^m, \nabla, i_{\text{max}}$)
22:     // Extract all dependent features on $i_{\text{max}}$
23:     $F_{i_{\text{max}}} \leftarrow \text{Family\_Dep}(i_{\text{max}})$
24:     // Family representative feature
25:     $j \leftarrow \text{Family\_Rep}(F_{i_{\text{max}}})$
26:     $\delta \leftarrow \nabla_j$ // Gradient of representative feature
27:     // Initialization function before updating dependencies
28:     $s \leftarrow \text{INIT\_FAMILY}(m, x^m, \nabla, j)$
29:     // Binary search for perturbation starting from gradient
30:     while $\delta \neq 0$ do
31:         $x^m_j \leftarrow x^m_j - \alpha \delta$ // Gradient update
32:         $x^m \leftarrow \text{UPDATE\_DEP}(s, x^m, \nabla, F_{i_{\text{max}}})$
33:         if $d(x^m, x^0) > d_{\text{max}}$ then
34:             // Reduce perturbation if outside feasible region
35:             $\delta = \delta/2$
36:         else
37:             return $x^m$

Our general evasion attack framework can be used for different classifiers, with different features and constraints. The components that need to be defined for each application are: (1) the optimization objective $G$ for computing adversarial examples; (2) the families of dependent features and family representatives; (3) the UPDATE\_DEP function that performs feature updates per family; (4) the projection operation to respect the physical-world constraints.

IV. EVASION ATTACKS FOR CONCRETE SECURITY APPLICATIONS

We describe in this section our framework instantiated to two cyber security applications, a malicious network connection classifier, and a malicious domain classifier. We emphasize that our framework is applicable to other security applications, such as malware classification, website fingerprinting, and malicious communication detection. For each of these, the application-specific constraints need to be encoded and respected when feature updates are performed.

A. Malicious Connection Classifier

Network traffic includes important information about communication patterns between source and destination IP addresses. Classification methods have been applied to labeled network connections to determine malicious infections, such as those generated by botnets [6], [11], [30], [43]. Network data comes in a variety of formats, but the most common include net flows, Bro logs, and packet captures.

Problem definition: dataset and features. We leverage a public dataset of botnet traffic that was captured in at the CTU University in the Czech Republic, called CTU-13 dataset [22]. The dataset include Bro connection logs with communications between internal IP addresses (on the campus network) and external ones. The dataset has the advantage of providing ground truth, i.e., labels of Malicious and Benign IP addresses. The goal of the classifier is to distinguish Malicious and Benign IP addresses on the internal network.

The fields available in Bro connection logs are given in Figure 2. They include: the timestamp of the connection start; the source IP address; the source port; the destination IP address; the destination port; the number of packets sent and received; the number of bytes sent and received; and the connection duration (the time difference between when the last packet and first packets are sent). A TCP connection has a well-defined network meaning (a connection established between two IP addresses using TCP), while for UDP Bro aggregates all packets sent between source and destination IPs in a certain time interval (e.g., 30 seconds) to form a connection.

We define features for an internal IP address based on the communication it has with external IPs on various ports following the approach from [42]. A standard method for creating network features is aggregation by destination port to capture relevant traffic statistics per port [22]. This is motivated by the fact that different network services and protocols run on different ports, and we expect ports to have different traffic patterns. We select a list of 17 ports for popular applications, including: HTTP (80), SSH (22), and DNS (53). We also add a category called OTHER for connections on other ports. We aggregate the communication on a port based on a fixed time window (the length of which is a hyper-parameter). For each port, we compute traffic statistics using operators such as Max, Min, and Total separately for outgoing and incoming connections. See the example in Figure 2, in which features
extracted for each port define a family of dependent features. These are statistical dependencies between features, which need to be preserved upon performing the attack. We obtain a total of 756 aggregated traffic features on these 17 ports.

**Physical constraints.** We assume that the attacker controls the victim IP on the internal network (e.g., it was infected by a botnet). The attacker thus can determine what network traffic the victim IP will generate. As there are many legitimate applications that generate network traffic, we assume that the attacker can only add network connections (a safe assumption to preserve the functionality of the legitimate applications).

When adding network connections, the attacker has some leverage in choosing the external IP destination, the port on which it communicates, the transport protocol (TCP or UDP), and how many packets and bytes it sends to the external destination. The attacker’s goal is to have his connection feature vector classified as Benign. When adding network connections, the attacker needs to respect physical constraints imposed by network communication, as outlined below:

1. Use TCP and UDP protocols only if they are allowed on certain ports. For example, on port 995 both TCP and UDP are allowed, but port 465 is specific to TCP.
2. The TCP and UDP packet sizes are capped at 1500 bytes. We thus create range intervals for these values: \([\text{tcp}_{\text{min}}, \text{tcp}_{\text{max}}]\) and \([\text{udp}_{\text{min}}, \text{udp}_{\text{max}}]\).
3. The duration of the connection is defined as the interval between when the last packet and the first packet is sent between source and destination. If the connection is idle for some time interval (e.g., 30 seconds), then it is closed by default in the Bro logs. The attacker can thus control the duration of the connection by sending packets at certain time intervals (to avoid closing the connection). We generate a range of valid protocol specific durations per packet range \([\text{tcp}_{\text{dmin}}, \text{tcp}_{\text{dmax}}]\) and \([\text{udp}_{\text{dmin}}, \text{udp}_{\text{dmax}}]\) from the distribution of connection duration in the training dataset.

**Attack algorithm.** The attack algorithm follows the framework from Algorithm 1, with the specific functions defined in Algorithm 2. First, the feature of maximum gradient is determined and the corresponding port is identified. The family of dependent features are all the features computed for that port. The attacker attempts to add a fixed number of connections on that port (which is a hyper-parameter of our system). This is done in the \texttt{INIT\_FAMILY} function (see Algorithm 2). The attacker can add either TCP, UDP or both types of connections, according to the gradient sign for these features and also respecting network-level constraints. The representative feature for a port’s family is the number of packets that the attacker sends in a connection. This feature is updated by the gradient value, following a binary search for perturbation \(\delta\), as specified in Algorithm \texttt{UPDATE\_FAMILY}.

In the \texttt{UPDATE\_DEP} function an update to the aggregated port features is performed. The difference in the total number of bytes sent by the attacker is determined from the gradient, followed by a projection operation to be within the feasible range for TCP and UDP packet sizes (function \texttt{PROJECT}). The \texttt{PROJECT} function takes an input a value \(x\) and a range \([a, b]\). It projects \(x\) to the interval \([a, b]\) (if \(x \in [a, b]\), it returns \(x\); if \(x > b\), it returns \(b\); otherwise it returns \(a\)). The duration is also set according to the gradient, again projecting based on lower and upper bounds computed from the data.
Algorithm 2 Malicious Connection Classifier Attack

Require: $x$: data point in iteration $m$

$p$: port updated in iteration $m$

$x_{TCP}/x_{UDP}$: number of TCP / UDP connections on $p$

$x^{\text{tot}}_{\text{bytes}}$: number of sent bytes on $p$

$x^{\text{min}}_{\text{bytes}}$: min number of sent bytes on port $p$

$x^{\text{max}}_{\text{bytes}}$: max number of sent bytes on port $p$

$x_{\text{dur}}/x_{\text{max}}$: total/min/max duration on $p$

$\nabla$: gradient of objective with respect to $x$

$c_1, c_2$: TCP and UDP connections added

1: function INIT_FAMILY($m, x^m, \nabla, i$)

// Add TCP connections if allowed
2: if $\nabla_{TCP} < 0$ and IS_ALLOWED(TCP, $p$) then
3: $x_{TCP} \leftarrow x_{TCP} + c_1$
4: UpdTCP $\leftarrow$ True

// Add UDP connections if allowed
5: if $\nabla_{UDP} < 0$ and IS_ALLOWED(UDP, $p$) then
6: $x_{UDP} \leftarrow x_{UDP} + c_2$
7: UpdUDP $\leftarrow$ True
8: return $s \leftarrow \langle \text{UpdTCP}, \text{UpdUDP} \rangle$

9: function UPDATE_DEP($s, x^m, \nabla, F_{\text{max}}$)

10: Let $s = \langle \text{UpdTCP}, \text{UpdUDP} \rangle$

11: // Compute gradient difference in sent bytes
12: $\Delta_b \leftarrow -\nabla_{\text{bytes}}$

13: if UpdTCP and UpdUDP then
14: // Project to respect physical constraints
15: $\Delta_b \leftarrow \text{PROJECT}(\Delta_b, c_1 \cdot \text{tcp}_{\text{min}} + c_2 \cdot \text{udp}_{\text{min}}, c_1 \cdot \text{tcp}_{\text{max}} + c_2 \cdot \text{udp}_{\text{max}})$

16: $n_{\text{conn}} \leftarrow c_1 + c_2$
17: else if UpdTCP then
18: $\Delta_b \leftarrow \text{PROJECT}(\Delta_b, c_1 \cdot \text{tcp}_{\text{min}}, c_1 \cdot \text{tcp}_{\text{max}})$

19: $n_{\text{conn}} \leftarrow c_1$

20: else
21: $\Delta_b \leftarrow \text{PROJECT}(\Delta_b, c_2 \cdot \text{udp}_{\text{min}}, c_2 \cdot \text{udp}_{\text{max}})$

22: $n_{\text{conn}} \leftarrow c_2$

23: $\Delta_{\text{bytes}} \leftarrow x_{\text{bytes}}^{\text{total}} + \Delta_b$

// Update Min and Max dependencies for sent bytes
24: $x_{\text{bytes}}^{\text{min}} \leftarrow \text{Min}(x_{\text{bytes}}^{\text{min}}, \Delta_b/n_{\text{conn}})$
25: $x_{\text{bytes}}^{\text{max}} \leftarrow \text{Max}(x_{\text{bytes}}^{\text{max}}, \Delta_b/n_{\text{conn}})$

// Update duration
26: $\Delta_d \leftarrow -\nabla_{\text{dur}}$

27: $\Delta_d \leftarrow \text{PROJECT}(\Delta_d, c_1 \cdot \text{tcp}_{\text{dmin}} \cdot \text{UpdTCP} + c_2 \cdot \text{udp}_{\text{dmin}} \cdot \text{UpdUDP}, c_1 \cdot \text{tcp}_{\text{dmax}} \cdot \text{UpdTCP} + c_2 \cdot \text{udp}_{\text{dmax}} \cdot \text{UpdUDP})$

28: $x_{\text{dur}}^{\text{total}} \leftarrow x_{\text{dur}}^{\text{total}} + \Delta_d$

29: $x_{\text{dur}}^{\text{min}} \leftarrow \text{Min}(x_{\text{dur}}^{\text{min}}, \Delta_d/n_{\text{conn}})$
30: $x_{\text{dur}}^{\text{max}} \leftarrow \text{Max}(x_{\text{dur}}^{\text{max}}, \Delta_d/n_{\text{conn}})$

| Feature | Description |
|---------|-------------|
| NIP     | Number of IPs connecting the domain |
| Num_Conn| Total number of connections |
| Avg_Conn| Average number of connections by an IP |
| Total_Send_Bytes | Total number of sent bytes |
| Total_Recv_Bytes | Total number of received bytes |
| Avg_Ratio_Bytes | Average ratio bytes sent over received by an IP |
| Min_Ratio_Bytes | Min ratio of bytes sent over received by an IP |
| Max_Ratio_Bytes | Max ratio of bytes sent over received by an IP |
| Frac_empty | Fraction of connections with empty content type |
| Frac_html | Fraction of connections with html content type |
| Frac_img | Fraction of connections with image content type |
| Frac_other | Fraction of connections with other content type |

TABLE II: Example families of features (Connections, Bytes, and Content) for malicious domains.

practice, this can be achieved by the attacker communicating with a non-existent remote IP, or communicating with an external IP under its control (for instance, the command-and-control IP controlled by the attacker). The other fields in Bro logs are not directly affecting the feature definition and can be sampled from the data (for instance, source port).

B. Malicious Domain Classifier

Problem definition: dataset and features. The second application is to classify domain names contacted by an enterprise hosts as Malicious or Benign. We use a dataset from [43], that was collected by a company that includes 89 domain features extracted from HTTP proxy logs and domain labels. The features come from 7 families, and we include an example of several families in Table II.

Attack algorithm. In this application, we do not have access to the raw HTTP traffic, only to features extracted from it. The majority of constraints are mathematical constraints in the feature space. The attack algorithm follows the framework from Algorithm 1, with the specific functions defined in Algorithm 3. The families of features have various dependencies, as illustrated in the Connection and Content families. For Connection we have statistical constraints (computing min, max, average values over a number of events), while for Content we have ratio constraints (ensuring that the sum of all ratio values equals to 1). We assume that we add events to the logs (and never delete or modify existing events). For instance, we can insert more connections, as in the malicious connection classifier. Function Update_Stat shows how the statistical features are modified, while function Update_Ratio shows how the ratio features are modified if a new event is added. We support other families of dependencies, among which one that has includes both statistical and ratio dependencies (see the definition of the ratio features for bytes sent over received). We omit here the details. The important observation here is that the constraints update functions are reusable across applications, and they can be extended to support new mathematical dependencies.
Algorithm 3 Malicious Connection Classifier Attack

Require: \( x \): data point in iteration \( m \)
1: function UPDATE\_DEP\((s, x^m, \nabla, F_{i_{\text{max}}}) \)
2: \quad if \( s == \text{Stat} \) then
3: \quad \quad Update\_Stat\((x^m, \nabla, F_{i_{\text{max}}}) \)
4: \quad if \( s == \text{Ratio} \) then
5: \quad \quad Update\_Ratio\((x^m, \nabla, F_{i_{\text{max}}}) \)
6: function Update\_Stat\((x^m, \nabla, F_{i_{\text{max}}}) \)
7: Parse \( F \) as: \( T \) (total number of events); \( N \) (number of entities); \( X_T, X_{\text{min}}, X_{\text{max}}, X_{\text{avg}} \) (the total, min, max, and average number of events per entity).
8: // \( X_T \) is representative feature.
9: \( X_T' \leftarrow \Pi(X_T - \alpha \nabla_T) \)
10: \( X_{\text{N+1}} \leftarrow X_T - \sum_{i=1}^{N} X_i \)
11: \( X_{\text{min}} \leftarrow \min(X_{\text{min}}, X_{\text{N+1}}) \)
12: \( X_{\text{max}} \leftarrow \max(X_{\text{max}}, X_{\text{N+1}}) \)
13: \( N \leftarrow N + 1; X_T \leftarrow X_T' \)
14: function Update\_Ratio\((x^m, \nabla, F) \)
15: Parse \( F \) as: \( \tilde{N}, \tilde{r}, X_1, \ldots, X_N \) such that: \( X_i = \frac{N_i}{\tilde{N}} \) and \( \sum_{i=1}^{\tilde{N}} X_i \).
16: // \( X_i \) is representative feature
17: \( N_r' \leftarrow \Pi(N_r - N) \)
18: \( N_{\text{prev}} \leftarrow N_r \leftarrow N + N_r' - N_r \)
19: \( X_r' \leftarrow \Pi(N_r' / N) \)
20: \( X_i \leftarrow ([X_i \cdot N]) / N, \forall i \neq r \)
21: \( N_r' \leftarrow N_r' \)

V. EXPERIMENTAL EVALUATION FOR MALICIOUS DOMAIN CLASSIFIER

The malicious domain dataset is larger and has more complex mathematical dependencies than the public malicious connection dataset. It offers us an opportunity to evaluate different optimization objectives and class imbalance ratios, as well as comparing with different baselines. We start with a description of the dataset in Section V-A, then we discuss ML model selection in Section V-B. In Section V-C we present results for the new attacks that overcome the limitations of the existing approaches. Next section we evaluate the malicious connection classifier.

A. Enterprise dataset

The data for training and testing the models was extracted from security logs collected by web proxies at the border of a large enterprise network with over 100,000 hosts. The number of monitored external domains in the training set is 227,033, among which 1730 are classified as Malicious and 225,303 are Benign. For training, we sampled a subset of training data to include all the Malicious domains, and a number of Benign domains to get several imbalance ratios between the two classes (1, 5, 15, 25, and 50). We used 500 Malicious domains and 500 Benign domains for testing the attack. Overall, the dataset includes 89 features from 7 categories. We assume that the attacker can modify the features from the Communication category, as well as other features that do not have dependencies, a total of 31 features (see Table XIII in Appendix for their description). These features are organized in four families: Connection, Bytes, HTTP Method, and Result code.

B. Model Selection

Hyper-parameter selection. We first evaluate three standard classifiers with different hyper-parameters (logistic regression, random forest, and FFNN). The hyper-parameters for logistic regression and random forests are in Tables XI and XII from the Appendix. For logistic regression, the maximum AUC score of 87% is achieved with \( L_1 \) regularization with inverse regularization 2.89. For random forest, the maximum AUC of 91% is obtained with Gini Index criterion, maximum tree depth 13, minimum number of samples in leaves 3, and minimum samples for split 8.

The architectures used for FFNN are illustrated in Table III. The best performance was achieved with 2 hidden layers with 80 neurons in the first layer, and 50 neurons in the second layer. ReLU activation function is used after all hidden layers except for the last layer, which uses sigmoid (standard for binary classification). We used the Adam optimizer and SGD with different learning rates. The best results were obtained with Adam and learning rate of 0.0003. We ran training for 75 epochs with mini-batch size of 32. As a result, we obtained the model with AUC score 89% in cross-validation accuracy.

| Hyperparameter | Value |
|----------------|-------|
| Architecture 1 layer | [80], [64], [40] |
| Architecture 2 layers | [80], [60], [80], [50], [80], [40], [64], [32], [48], [32] |
| Architecture 3 layers | [80], [60], [40] |
| Optimizer | Adam, SGD |
| Learning Rate | [0.0001, 0.01] |

TABLE III: DNN Architectures, epochs = 75

Model comparison. After performing model selection for each type of model, we compare the three best resulting models. Figure 3a shows the ROC curves and AUC scores for a 1:1 imbalance ratio (with the same number of Malicious and Benign points used in training). The performance of FFNN is slightly worse than that of random forest, but it might be possible to improve these results with additional effort (note that for higher imbalance ratio the performance of FFNN improves, as shown in Figure 3b). For the remainder of the section, we focus our discussion on the robustness of FFNN models.

Comparison of class imbalance for FFNN. Since the issue of class imbalance is a known challenge in cyber security [6], we analyze the model accuracy as a function of imbalance ratio, showing the ROC curves in Figure 3b. Interestingly, the performance of the model increases to 93% AUC for imbalance ratio up to 25, after which it starts to decrease (with AUC of 83% at a ratio of 50). Our intuition is that the FFNN model achieves better performance when more training data is available (up to a ratio of 25). But once the Benign
class dominates the Malicious one (at ratio of 50), the model performance starts to degrade.

C. Robustness to evasion attacks

After we train our models, we use a testing set of 500 Malicious and 500 Benign data points to evaluate the attack success rate. We vary the maximum allowed perturbation expressed as an $L_2$ norm and evaluate the success of the attack. We evaluate the two optimization objectives for Projected and Penalty attacks and compare with several baselines. We also run directly the C&W attack and show that it results in infeasible adversarial examples (as expected). We evaluate the success rate of the attacks for different imbalance ratios. We also perform some analysis of the features that are modified by the attack, and if they correlate with feature importance. Finally, we show an adversarial example generated by our method.

Existing Attack. We run the existing C&W attack [12] on our data in order to measure if the adversarial examples are feasible. While the performance of the attack is high and reaches 98% at distance 20 (for the 1:1 balanced case), the resulting adversarial examples are outside the feasibility region. An example is included in Table IV, showing that the average number of connections is not equal to the total number of connections divided by the number of IPs. Additionally, the average ratio of received bytes over sent bytes is not equal to maximum and minimum values of ratio (as it should be when the number of IPs is 1).

Projected attack results. We evaluate the success rate of the attack with Projected objective first for balanced classes (1:1 ratio). We compare in Figure 4a the attack against two baselines: Baseline 1 (in which the features that are modified iteratively are selected at random), and Baseline 2 (in which, additionally to random feature selection, the amount of perturbation is sampled from a standard normal distribution $N(0, 1)$). The attacks are run on 412 Malicious examples that are classified correctly by the FFNN. The Projected attack improves both baselines, with Baseline 2 performing much worse, reaching success rate 57% at distance 20. By selecting the amount of perturbation according to our algorithm, Baseline 1 gets an attack success rate of 91.7% at distance 20, compared to the Projected attack success of 98.3% at the same distance. This shows that the attacks is still performing reasonably if feature selection is done randomly, but it is very important to add perturbation to features consistent with the optimization objective.

We also measure in Figure 4b the decrease of the model’s performance with and without the presence of the attack at different perturbation upper bounds (using 500 Malicious and 500 Benign examples). While AUC score is 0.87 without the attack, it drastically decreases to 0.52 already at $L_2$ distance 7. This shows the significant degradation of the model’s performance under attack.

Finally, we ran the attack at different imbalance ratios and measured its success rate with respect to maximum allowed perturbation. The results are illustrated in Figure 4c. In this experiment, we select 62 test examples which all models (trained for different imbalance ratios) classified correctly before the attack. At the $L_2$ distance of 20 the attack achieves 100% success rate for all ratios except 1. Additionally, we observe that with higher imbalance, it is easier for the attacker
to find adversarial examples (at fixed maximum distance). One reason for this is that models that have lower performance initially (as the one trained with 1:50 imbalance ratio) are easier to attack. Second, we believe that as the imbalance gets higher the model becomes more biased towards the majority class (Benign), which is the target class of the attacker in our case, and it is easier to cross the decision boundary between classes (independent of the model’s accuracy).

**Penalty attack results.** We now discuss the results achieved by applying our attack with the Penalty objective on the testing examples. Similar to the Projected attack, we compare the success rate of the Penalty attack to the two types of baseline attacks (for balanced classes), in Figure 5a (using the 412 Malicious testing examples classified correctly). Overall, the Penalty objective is performing worse than the Projected one, reaching 79% success rate at $L_2$ distance of 20. We observe that in this case both baselines perform worse, and the attack improves upon both baselines significantly. The decrease of model’s performance under the Penalty attack is illustrated in Figure 5b (for 500 Malicious and 500 Benign testing examples). While AUC is 0.87 before the attack, it decreases to 0.59 already at distance 7. Furthermore, we measure the attack success rate at different imbalance ratios in Figure 5c (using the 62 testing examples classified correctly by all models). For each ratio value we searched for the best hyper-parameter $c$ between 0 and 1 with step 0.05. Here, as with the Projected attack, we see the same trend: as the imbalance ratio gets higher, the attack performs better, and it works best at imbalance ratio of 50.

**Attack comparison.** We compare the success rate of the two objectives (Projected and Penalty) with the C&W attack, as well as an attack we call Post-processing. The Post-processing attack runs directly the original C&W developed for continuous domains, after which it projects the adversarial example to the feasible space to enforce the constraints. In the Post-processing attack, we look at each family of dependent features, keep the value of the representative feature as selected
by the attack, but then modify the values of the dependent fea-
tures using the UPDATE_DEP function. The success rate of
test all these attacks is shown in Figure 6, using the 412 Malicious
testing examples classified correctly. The attacks based on our
framework (with Projected and Penalty objectives) perform
best, as they account for feature dependencies during the
adversarial point generation. The attack with the Projected
objective has the highest performance (we suspect that the
Penalty attack is sensitive to parameter c). The vanilla C&W
has slightly worse performance at small perturbation values,
even though it does not take into consideration the feature
constraints and works in an enlarged feature space. Interest-
ingly, the Post-processing attack performs worse (reaching
only 0.005% success at distance 20 – can generate 2 out of
412 adversarial examples). This demonstrates that it is not
sufficient to run state-of-art attacks for continuous domains and
then adjust the feature dependencies, but more sophisticated
attack strategies are needed.

Number of features modified. We compare the number
of features modified during the attack iterative algorithm to
construct the adversarial examples for three attacks: Projected,
Penalty, and C&W. The histogram for the number of modified
features is illustrated in Figure 7a. It is not surprising that
the C&W attack modifies almost all features, as it works
in $L_2$ norms without any restriction in feature space. Both
the Projected and the Penalty attacks modify a much smaller
number of features (4 on average).

We are interested in determining if there is a relationship
between feature importance and choice of feature by the attack.
For additional details on feature description, we include the list
of features that can be modified in Table XIII in the Appendix.
In Figure 7b we plot the number of modifications for each fea-
ture (left axis) and feature importance (right axis). We observe
that feature importance is correlated with the attack’s feature
choice. However, since we are modifying the representative
feature in each family, the number of modifications on the
representative feature is usually higher (it accumulates all the
importance of the features in that family). For the Bytes family,
feature 3 (number of received bytes) is the representative
feature and it is updated more than 350 times. However, for
features that have no dependencies (e.g., 68 – number of levels
in the domain, 69 – number of sub-domains, 71 – domain
registration age, and 72 – domain registration validity), the
number of updates is correlated with feature importance.

Adversarial examples. Finally, we include an adversarial
example in Table V for the Projected attack. We only show
the features that are modified by the attack and their origi-
nal value. As we observe, the attack preserves the feature
dependencies: the average ratio of received bytes over sent
bytes (Avg_Ratio_Bytes) is consistent with number of received
(Bytes_Recv_Bytes) and sent (Bytes_Sent_Bytes) bytes. In
addition, the attack modifies the domain registration age, a
relevant feature in malicious domain classification [40].

| Feature             | Original | Adversarial |
|---------------------|----------|-------------|
| Total_Recv_Bytes    | 32.32    | 43653.50    |
| Total_Sent_Bytes    | 2.0      | 2702.62     |
| Avg_Ratio_Bytes     | 16.15    | 16.15       |
| Registration_Age    | 349      | 3616        |

TABLE V: Adversarial example for the Projected attack (dis-
tance 10).

VI. EXPERIMENTAL EVALUATION FOR MALICIOUS
CONNECTION CLASSIFIER

| Hyperparameter   | Value       |
|------------------|-------------|
| Architecture     | [256, 128, 64] |
| Optimizer        | Adam        |
| Learning Rate    | 0.00026     |

TABLE VI: DNN Architecture

| Training scenario | F1   | AUC  |
|-------------------|------|------|
| 1, 2              | 0.94 | 0.96 |
| 1, 9              | 0.96 | 0.97 |
| 2, 9              | 0.83 | 0.79 |

TABLE VII: Training results for FFNN.

In this application we have access to raw network con-
nections (in Bro log format), which provides the opportunity
to generate feasible adversarial examples. We show how an attacker can insert new realistic network connections to change the prediction of Malicious activity. We only analyze the Projected attack here, as it demonstrated best performance in the previous application. The code of the attack is available at https://github.com/achernikova/cybersecurity_evasion. For the attack against malicious domain classifier the dataset is proprietary and we cannot release the code.

We start with a description of the CTU-13 dataset in Section VI-A, then we show the performance of FFNN for connection classification in Section VI-B. Finally, we present the analysis on model robustness in Section VI-C.

A. CTU-13 dataset

CTU-13 is a collection of 13 scenarios including both legitimate traffic from the campus network, as well as labeled connections of malicious botnets [22]. We restrict to three scenarios for the Neris botnet (1, 2, and 9). We choose to train on two of the scenarios and test the models on the third, to guarantee independence between training and testing data. The training data has 3869 Malicious examples, 194,259 Benign examples, and an imbalance ratio of 1:50. There is a set of 432 statistical features that the attacker can modify (the ones that correspond to the characteristics of sent traffic). The physical constraints and statistical dependencies on bytes and duration have been detailed in Section IV-A.

B. Classification results

We perform model selection and training for a number of FFNN architectures on all combinations of two scenarios, and tested the models for generality on the third scenario. The best architecture is illustrated in Table VI. It consists of three layers with 256, 128 and 64 hidden layers. We used the Adam optimizer, 50 epochs for training, mini-batch of 64, and a learning rate of 0.00026. The F1 and AUC scores for all combinations of training scenarios are illustrated in Table VII. We also compared the performance of FFNN with logistic regression and random forest, but we omit the results (FFNN achieved similar performance to random forest). For the adversarial attacks, we choose the scenarios with best performance: training on 1, 9, and testing on 2.

C. Robustness to evasion attacks

We show the Projected attack’s performance, discuss which ports were updated most frequently, and show an adversarial examples and the corresponding Bro logs records. The testing data for the attack is 407 Malicious examples from scenario 2, among which 397 were predicted correctly by the classifier.

Attack performance. First, we analyze the attack success rate with respect to the allowed perturbation, shown in Figure 8a. The attack reaches 99% success rate at $L_2$ distance 16. Interestingly, in this case the two baselines perform poorly, demonstrating the clear advantages of our framework. We plot next the ROC curves under attack in Figure 8b (using the 407 Malicious examples and 407 Benign examples from scenario 2). At distance 8, the AUC score is 0.93 (compared to 0.98 without the attack), but there is a sudden change at distance 10, with AUC score dropping to 0.77. Moreover, at distance 12, the AUC reaches 0.12, showing the significant degradation under attack with relatively small distance.

Ports family statistics. We show the average number of port families updated during the attack in Figure 8c. The maximum number is 3 ports (at smaller distance), but it decreases to 1 port at distance higher than 12. While counter-intuitive, this can be explained by the fact that at larger distances the attacker can add larger perturbation to the aggregated statistics of one port, crossing the decision boundary.

In Table X we include the port families selected during attack, at distance 8, as well as their importance. The port importance was computed by summing up the importances of all the features in the port’s family. Ports 443, 80, and OTHER were updated most frequently, and have highest importance.
TABLE IX: Example of legitimate Bro logs records for scenario 2 (top 3 rows), and Bro connection log added to create adversarial example (bottom row).

| Port Number | Number of Updates | Port Importance |
|-------------|-------------------|-----------------|
| 1           | 2                 | 7.2 e-04        |
| 22          | 63                | 6.1e-04         |
| 80          | 349               | 9.0e-03         |
| 123         | 9                 | 1.1e-03         |
| 443         | 387               | 3.9e-03         |
| OTHER       | 363               | 3.9e-02         |

TABLE X: Port updated at distance 8.

Adversarial examples. We show an adversarial example generated by the Projected attack at distance 14. Table VIII includes the original feature values and their modifications (on port 443). The attacker adds only 12 TCP connections on port 443, including 87 packets, each of size 1292 bytes, with connection duration of 432.47 seconds. There are 12 additional records in the Bro connection logs generated by the attack (see an example in Table IX). The destination IP can be selected by the attacker so that it does not exist or it does not respond (we assumed the number of received bytes and packets is 0). Interestingly, all adversarial attacks succeed with at most 12 new connections for distances higher than 10.

VII. RELATED WORK

Adversarial machine learning is a field that studies the vulnerabilities of ML against attacks [31]. Research on the robustness of DNNs at testing time started with the work of Biggio et al. [9] and Szegedy et al. [55]. They showed that classifiers are vulnerable to adversarial examples generated with minimal perturbation to testing inputs. Since then, the area of adversarial ML has received a lot of attention, with recent research on certified defenses [50], [51] and by a Google Security and Privacy Award. This research project was funded by NSF under grant CNS-1717634.

Evasion attacks in security. Several evasion attacks have been proposed against models with discrete and constrained input vectors, as encountered in security applications.

The majority of these use datasets with binary features, not considering dependencies in feature space. Biggio et al. [9] use a gradient-based attack to construct adversarial examples for malicious PDF detection by only adding new keywords to PDFs. Grosse et al. [26] leverage the JSMA attack by Papernot et al. [45] for a malware classification application in which features can be added or removed. Suciu et al. [54] add bytes to malicious binaries either at the end or in slack regions to create adversarial examples. Kreuk [34] discover regions in executables that would not affect the intended malware behavior. Kolosnjaji et al. [33] create gradient-based attack against malware detection DNNs that learn from raw bytes, and can create adversarial examples by only changing few specific bytes at the end of each malware sample.

Xu et al. [61] propose a black-box attack based on genetic algorithms for manipulating PDF files, while maintaining the required format. Dang et al. [16] propose a black-box attack against PDF malware classifiers that uses hill-climbing over a set of feasible transformations. Anderson et al. [2] construct general black-box framework based on reinforcement learning for attacking static portable executable anti-malware engines. Kulynych et al. [35] propose a graphical framework for discrete domains with guarantees of minimal adversarial cost.

None of the previous work can handle the complex dependencies encountered in security datasets, and meet physical-world constraints to generate feasible adversarial examples.

Evasion attacks in other domains. There is work on designing attacks in other domains, such as video: [23], [14], [63], [52], [49], [62], [13], [48]; text: [46], [17], [39], [21], [1]; and audio: [38], [29], [59]. Physically realizable attacks have been designed for face recognition [50] and vision [18].

Certified defenses. Recent research on certified defenses against evasion attacks aims to obtain provable guarantees of error under attack under worst-case adversaries. [7], [15], [19], [28], [37], [58]. Robustness is the proof that the model's decision is stable in the $L_p$ ball around the input vector. However, all this work considers continuous domains such as images, and is difficult to extend to discrete domains.

VIII. CONCLUSIONS

The absence of robustness guarantee in FFNNs limit the application of Deep Learning in the variety of critical applications. We showed that evasion attacks against feed-forward neural networks are a real threat for cyber security applications. We proposed a general framework that can create adversarial examples respecting mathematical dependencies and physical-world constraints imposed by security applications. We demonstrated evasion attacks that insert a small number of connections (12 records in Bro connection logs) to mis-classify Malicious activity as Benign in a malicious connection classifier. Future work in this space includes the design of reliable defenses with provable guarantees, as well as exploring attackers with more limited capabilities (e.g., black-box attacks).

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We include the hyper-parameters for logistic regression and random forest in Tables XI and XII, respectively.

### TABLE XI: Logistic Regression

| Hyperparameter          | Value               |
|-------------------------|---------------------|
| Regularization Norm     | L1, L2              |
| Inverse of regularization strength | [0.01, 100]         |

### TABLE XII: Random Forest

| Hyperparameter | Value |
|----------------|-------|
| Criterion      | Entropy, Gini Index |
| Tree depth     | [2, 19], step = 1  |
| Split range    | [2, 9], step = 1   |
| Leaf range     | [1, 5], step = 1   |

We include the set of features that can be modified for the malicious domain classifier in Table XIII and for the malicious network connection classifier in Table XIV.
| Category | Feature | Description |
|----------|---------|-------------|
| Connections | Num_Conn | Number of established connections |
| Connections | Avg_Conn | Average number of connections per host |
| Bytes | Total_Receivables | Total number of received bytes |
| Bytes | Total_Sent | Total number of sent bytes |
| Bytes | Avg_Ratio | Average ratio of received bytes over sent bytes per IP |
| Bytes | Min_Ratio | Minimum ratio of received bytes over sent bytes per IP |
| Bytes | Max_Ratio | Maximum ratio of received bytes over sent bytes per IP |
| HTTP Method | Num_POST | Total number of POST requests |
| HTTP Method | Num_GET | Total number of GET requests |
| HTTP Method | Avg_POST | Average number of POST requests over GET requests per IP |
| HTTP Method | Min_POST | Minimum number of POST requests over GET requests per IP |
| HTTP Method | Max_POST | Maximum number of POST requests over GET requests per IP |
| Result Code | Num_200 | Number of connections with result code 200 |
| Result Code | Num_300 | Number of connections with result code 300 |
| Result Code | Num_400 | Number of connections with result code 400 |
| Result Code | Num_500 | Number of connections with result code 500 |
| Result Code | Frac_200 | Fraction of connections with result code 200 |
| Result Code | Frac_300 | Fraction of connections with result code 300 |
| Result Code | Frac_400 | Fraction of connections with result code 400 |
| Result Code | Frac_500 | Fraction of connections with result code 500 |
| Independent | Avg_OS | Average number operating systems extracted from user-agent |
| Independent | Avg_Browser | Average number of browsers used |
| Independent | Dom | Number of domains |
| Independent | Sub_Domains | Number of sub-domains |
| Independent | Length | Length of domain |
| Independent | WHOIS Reg_Age | WHOIS registration age |
| Independent | WHOIS Reg_Valid | WHOIS registration validity |
| Independent | WHOIS Update_Age | WHOIS update age |
| Independent | WHOIS Update_Valid | WHOIS update validity |
| Independent | Num_ASN | Number of ASNs |
| Independent | Num_Countries | Number of countries contacted the domain |

TABLE XIII: Features definition for malicious domain classification.

| Category | Feature | Description |
|----------|---------|-------------|
| Bytes | Total_Sent | Total number of bytes sent |
| Bytes | Min_Sent | Minimum number of bytes sent per connection |
| Bytes | Max_Sent | Maximum of bytes sent per connection |
| Packets | Total_Pkts | Total number of packets sent |
| Packets | Min_Pkts | Minimum number of packets sent per connection |
| Packets | Max_Pkts | Maximum of packets sent per connection |
| Duration | Total_Duration | Total duration of all connections |
| Duration | Min_Duration | Minimum duration of a connection |
| Duration | Max_Duration | Maximum duration of a connection |

TABLE XIV: Features definition for malicious connection classification. These features are defined for each port by aggregating over all connections on that port in a fixed time window.