EVAGAN: Evasion Generative Adversarial Network for Low Data Regimes

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I. INTRODUCTION

Low data regimes are found in many real-life applications in which researchers face data scarcity problems [1]. The data scarcity pertains to the situation where one class is abundant in data samples (especially normal behaviour) while the anomaly samples are rare and difficult to gather [2]. The data scarcity can also be described as a data imbalance problem potentially resulting in decision bias in the machine learning (ML) classifiers. The network traffic datasets are one of the prime examples of data imbalance problems. Since the ML intrusion detection systems are data-hungry probabilistic models, having more data can improve their performance [3]. There can be two ways of gathering the attacks data. The first is to emulate the real attacks using dedicated machines in a lab environment using open-source operating systems like Kali Linux [4], [5]. There are two main disadvantages of generating real data: First, real data gathering can be expensive to simulate the attacks using multiple hardware resources. Second, the spawned attacks may not accurately represent a real attack scenario. The second way is to generate data synthetically, which can be relatively cost-efficient [6].

Synthetic data generation is also termed data oversampling. Using generative adversarial networks (GANs) as synthetic oversamplers has been a voguish research endeavour for low data regimes [3], [7]. Various researchers have demonstrated that GANs are more effective as compared to other synthetic oversamplers like SMOTE [2], [6], [8], [9]. It is found in many studies that due to the adversarial factor, GANs can better estimate the target probability distribution [2], [8], [10]. In a simple/vanilla GAN, two different neural networks generator \( G \) and discriminator \( D \) work antagonistically to learn from each other’s experience to converge to Nash equilibrium [11]. As an oversampler, after being trained to a certain number of epochs, \( G \) is used to generate additional data. Depending on how well a GAN learned the input data probability distribution, the close resembling data is annexed to the original train set. This process is called data augmentation (DA), which many researchers have demonstrated to be effective in improving the detection performance of ML classifiers [12]–[16].

Since AI-based systems are prone to adversarial evasion attacks, it is imperative to harden the ML classifiers against adversarial evasions. Black box attackers can use GANs to generate evasion samples [14], [15], [17]. Therefore, employing GANs can be an effective technique to design an adversarial aware classifier resulting from DA proactively. Although DA is effective in helping the ML classifiers recognize the
perturbed data samples, $D$ of a GAN can be extended to act as a multiclass classifier so that it can be used as an anomaly detector [15], [18], [19]. In this way, we do not need to use DA as the $D$ is trained simultaneously with $G$. Auxiliary Classifier GAN (ACGAN) is an example of such a GAN in which the $D$ not only differentiates between fake and real samples but also can be used as a multiclass classifier [2], [20]. The advantage of extending the $D$ in ACGAN is to improve training stability and quality of generated samples [20]. In this work, with the help of experimentation, we have demonstrated that ACGAN does not perform well in highly unbalanced datasets. So we propose a novel GAN based on ACGAN called EVAGAN that outperforms ACGAN in terms of detection performance, stability in training and time complexity.

We summarise the main contributions of this paper in the following aspects:

1) We propose a novel GAN model to design an evasion-aware discriminator as a sophisticated botnet detector.
2) We demonstrate by experiments that the existing use of ACGAN to design a sophisticated classifier can fail in highly unbalanced datasets.
3) We demonstrate that EVAGAN outperforms ACGAN in terms of performance detection, stability and time complexity for cybersecurity (CC) botnet and computer vision (CV) datasets.

The rest of this paper has been organized as follows. Section II provides a comprehensive background of vanilla GANs, data oversampling, adversarial evasion and ACGAN, section III presents the details of the proposed model, section IV gives a description of implementation details, section V demonstrates the results, section VI provides an analysis of the results and section VII concludes the paper.

II. BACKGROUND

A. Generative Adversarial Networks (GANs)

The GAN is a combination of two different neural networks, each having a unique structure. The one responsible for generating synthetic samples is called generator ($G$), and the other that evaluates the generated samples is called discriminator ($D$). Figure 1 shows the block diagram of a classical/vanilla GAN. There are two subsequent steps in which a GAN is trained. In the first step, the $D$ is trained on real data, and the data generated by an untrained $G$ labelled as REAL and FAKE subsequently. In the next step, now that the $D$ has trained already, it is tested on the fake data from $G$ labelled as REAL. The loss of the $D$ on this falsely labelled data is fed back to the $G$ which adjusts its weights in one complete batch training. There can be several batch iterations, after which one complete traversal of the dataset is complete, also known as an epoch.

In the classical GAN, the generator model can be represented as $G:z \rightarrow \mathcal{X}$ where $z$ is the normal distribution from noise space and $\mathcal{X}$ is the real data distribution.

The discriminator $D:\mathcal{X} \rightarrow [0,1]$ model is a classifier that outputs an estimate of probability between 0 and 1, to mark whether the data coming from $G$ is real or fake. The objective function of the combined model can be represented by

$$\min_{G} \max_{D} V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_{z}(z)}[\log (1 - D(G(z)))]$$

Here, $\mathbb{E}$ represents the expected value of the loss and $x$ and $z$ denote the real and noise samples, respectively. At the same time, $p_z$ and $p_{data}$ are the probability distributions of noise and real data, respectively. The objective of a min-max game is to minimize the generator’s loss in creating data resembling the real data since the generator can not control the loss of $D$ on real data. Still, it can maximize the loss of $D$ on generated data $G(z)$. The objective function of $G$ is given by Equation 2.

$$J_G(G) = \mathbb{E}_{z \sim p_{z}(z)}[\log(D(G(z)))]$$

As demonstrated in the Figure 1, the losses of $D$ on real $D_{\text{Loss}}$ and generated data, $D_{\text{Loss}}(\text{FAKE})$ are fed to $D$ using back-propagation. In the next step, in forward propagation, given label as REAL to the input generated samples (coming from $G$), the evaluation is done by $D$ and $G_{\text{Loss}}(\text{REAL})$, is fed back to $G$ to update its weights. This step is called the combined model training. The combined model is the structure of a GAN in which the output of the $D$ is fed back to $G$ so that only the weights of the $G$ are updated. This process keeps iterating till the number of epochs reaches a set value. Upon achieving the Nash equilibrium, the generator and discriminator do not learn further.

B. Data Oversampling & GANs

In low data regimes, oversampling or undersampling can help balance the datasets. However, undersampling might result in the loss of diversity. For oversampling, methods like SMOTE use nearest neighbours and linear interpolation, which can be unsuitable for high-dimensional and complex probability distributions [8], [21]. Recent research works proposed algorithms for data oversampling. Authors in [22] compared 85 different oversampling techniques and suggested three best-performing variants as SMOTE_IPF, ProWSyn and polynomial_fit_SMOTE. In [6], authors have compared the performance of these three SMOTE variants with GANs. Through empirical results, they found that GANs outperform the three
mentioned oversamplers in most of the adversarial training of ML classifiers.

C. Adversarial Evasion & GANs

The decision bias in ML classifiers can lead to misclassification of malicious samples as normal. The attackers can exploit this intrinsic nature of ML classifiers to incarnate evasion samples, particularly in low data regimes. The adversarial evasion is a perturbed version of an input sample $j$ as $j^*$ such that the $j^* = j + \eta$, where $\eta$ is a carefully crafted perturbation. When making an adversarial attack, $\eta$ could be sought and selected so that the classifier cannot discriminate the $j^*$ from $j$ [23], [24]. The researchers usually employ adversarial training to make the classifiers proactively aware of the evasion samples. However, this is not needed if we use the $D$ of a GAN as a classifier to differentiate not only between the fake and real samples but also between normal and anomaly samples. The fake samples generated by the $G$ are also learnt at the same time, so it is better to consider the power of $D$ as an evasion aware classifier. We do not need to use extra ML classifiers, which is a common practice in various literary works to design such a classifier [18], [19].

To this end, we propose EVAGAN that provides such type of $D$ and compare its performance with the $D$ of ACGAN and other ML classifiers, xgboost (XGB), decision tree (DT), naive Bayes (NB), random forests (RF), logistic regression (LR) and k-nearest neighbours (KNN). Following rigorous experimentation, we explore that EVAGAN’s $D$ not only outperforms the ML classifiers in black box testing but also gives 100% accuracy in normal and evasion samples estimation. The details of the experimental results will be discussed in section VI.

D. ACGAN

ACGAN extends a classical GAN exploiting class labels in the training process [20]. Similar to a classical GAN, ACGAN includes two neural networks: a Generator ($G$) and a Discriminator ($D$). In addition to random noise $z$, the input of $G$ includes a class label $c$. Therefore, the synthesized sample from $G$ in ACGAN is $X_{fake} = G(c, z)$, instead of $X_{fake} = G(z)$. In other terms, a desired class label data can be generated by an ACGAN. So the $D$ of ACGAN works as a dual classifier for differentiating between the real/fake data and different classes of the input samples whether coming from the real source or the $G$.

The objective function of ACGAN consists of two parts: The first is the log-likelihood $L_S$ of the correct source data, and the second is the log-likelihood $L_C$ of the correct class labels. $D$ is trained to maximize $L_C + L_S$ and $G$ learns to maximize $L_C - L_S$. In other words, the objective of $D$ is to improve the two likelihoods while of $G$ is to improve only one likelihood, i.e. to improve the performance of $D$ on classifying the samples as different class labels. $G$ will also try to suppress the log-likelihood by the $D$ on a fake sample correctly classified as fake, i.e. it will try to fool the $D$. $D$ gives both a probability distribution over sources and the

\[
L_S = \mathbb{E}[\log P(S = real|X_{real})] + \mathbb{E}[\log P(S = fake|X_{fake})]
\]

\[
L_C = \mathbb{E}[\log P(C = c|X_{real})] + \mathbb{E}[\log P(C = c|X_{fake})]
\]

A careful observation of Figure 2 suggests that there seems to be no tremendous difference between ACGAN and EVAGAN; however, the significance of simple modifications in the generator input, discriminator output and loss functions is discussed in more detail in section III.

III. EVAGAN

In this section, we discuss the design of EVAGAN, the structural explanation of its generator and discriminator, along with the objective and loss functions.

A. Problem Statement

Considering the generator ($G$) of ACGAN, $X_{fake} = G(c, z)$ where $c$ is the class label, $G$ has to generate the labels of all classes. Hence the number of the samples generated by $G$ may include $C = \{c_1, c_2, c_3, ..., c_n\}$ which may not be a requirement in low data regimes. Since we only need to generate a low sample class $c_m$ instead of all the classes, so the generator does not need to be aware of the classification performance of $D$ on majority class samples. In this way, the training time of $G$ is reduced as the diversity seen by the $G$ is less complex to generate a single class sample. Due to this reason, we can not only improve the performance of the $G$ but also can harden the $D$ simultaneously with fewer $c_m$ labels. The ratio of the different class labels can vary depending on the performance of $G$ as this is a stochastic process. However, in most cases, the majority class samples will be more than the minority samples. Note that EVAGAN design is dedicated to binary class problems where the samples of a minority class are scanty. For using EVAGAN for multiclass cases, each anomaly class should be considered separately from the normal class to make it a binary classification problem. However, the concept can be extended to multiclass that we leave to future work.
B. Architecture

The design of EVAGAN has been inspired by ACGAN as we want to develop a classifier model that hardens itself on the GAN generated evasion samples. The main structure of EVAGAN consists of two neural networks; the generator $G$ and the discriminator $D$. In contrast to ACGAN, EVAGAN’s model is limited to labels from a single class embedded with noise as the input to the generator ($G$). The details of the $G$ have been explained in subsection III-C. Figure 3 shows the detailed architecture of EVAGAN. The REAL and FAKE labels in blue colour show input labelling for the first step of EVAGAN training, and the REAL label in red represents the training of the combined model as a second step. These two steps of a typical GAN training were expressed earlier in subsection II-A. The discriminator $D$ of EVAGAN has three different outputs for the estimation of majority, minority and fake/real classes. Sigmoid functions have been used for the three outputs, each with binary cross-entropy (BCE) loss. The details of $D$ are further expressed in subsection III-D. The loss functions have also been mentioned in respective subsections of the $G$ and $D$.

Figure 3 shows a green outlined box on the right side to show the three different probability estimations as outputs from $D$. These three estimations are used to compute the loss of $D$ in the first step of EVAGAN training. An orange outlined box including the real/fake estimation and minority class estimation computes the $G_{Loss}$ to be fed back to the $G$ in the backpropagation of the combined model training (second step of EVAGAN training). Note that the output of the $D$ is distributed using three different sigmoid units to separate the probabilities of each class, i.e. majority, sources (real/fake) and minority. The majority and minority class estimations could be combined using a single sigmoid function. However, keeping them separate has three advantages. The first is to avoid the loss of the majority class being fed back to the $G$. Second, it simplifies the model with no extra training cost. Third, we can conveniently separate the predictions for the test set samples, which will be discussed in Section V.

C. Generator

The generator ($G$) of EVAGAN only takes noise $n$ and the single class labels $c = 1$. The labels are embedded in the input layer of the $G$. The objective function of the $G$ has two parts as shown in Equations 5 and 6.

$$I^G(G) = E_{z \sim p_z(z)}[\log(D(G(z)))]$$

(5)

$$J^G(G) = E_{c_m \sim y_m}[\log P(C = c_m | \mathcal{X}_{m_{fake}})]$$

(6)

The Equation 5 is the objective function of $G$ to minimize the log-likelihood of the fake samples generated by $G$ as fake similar to Equation 2. In Equation 6, $J^G(G)$ is the objective function of $G$ for improving the log-likelihood of minority class samples coming from the $G$ into the $D$. Here, $y_m$ denotes the minority class label in the real dataset, and $P$ is the output probability from $D$. Since the $G$ only needs to generate $c_m$ samples so it should only receive the loss of $D$ on the estimation of minority class and the sources, i.e. the samples being real or fake. The objective function of $G$ is to maximize the $D$ loss on sources. At the same time, it will assist in minimizing the $D$ loss on $c_m$ samples. Equation 7 shows the objective function of $G$.

$$L^G(G) = argmax(J^G(G) - I^G(G))$$

(7)

The cross-entropy (CE) loss of two different probability distributions $p(x)$ and $q(x)$ can be denoted using Equation 8, where $x$ denotes the samples belonging to the $\mathcal{X}$ dataset.

$$CE(p, q) = - \sum_{x \in \mathcal{X}} p(x) \log q(x)$$

(8)

Let $y_{x_i}$ be the actual probability distribution of sample $x_i$ in dataset $\mathcal{X}$, $P(S = \text{fake}|\mathcal{X}_{m_{fake}})$ be the predicted probability distribution of generated samples being fake and $P(C = c_m|\mathcal{X}_{m_{fake}})$ be the predicted probability distribution...
from $\mathcal{D}$ for minority class $c_m$, then the loss function of $\mathcal{G}$ for $N$ samples will be given by the Equation 9.

$$G_{\text{Loss}} = -\frac{1}{N} \sum_{i=1}^{N} \left[ y_{zi}^{\text{fake}} (\log P(S = \text{fake}|\mathcal{X}_{m_{\text{fake}}})) + y_{zi}^{\text{real}} (1 - \log P(C = c_m|\mathcal{X}_{m_{\text{fake}}})) \right]$$  \hspace{1cm} (9)$$

In Equation 9, $y_{zi}^{\text{fake}}$ is the actual probability distribution for the fake samples generated by $\mathcal{G}$ and $y_{zi}^{\text{real}}$ is the actual class probability of minority class. These two terms can also be expressed as the actual labels for fake and minority classes. According to Equation 9, the utmost desire of $\mathcal{G}$ is to minimize the $G_{\text{Loss}}$, so it tends to reduce the prediction of $\mathcal{D}$ on fake samples as much as possible by suppressing the term $\log P(S = \text{fake}|\mathcal{X}_{m_{\text{fake}}})$. As the second objective, it will try to increase the value of $\log P(C = c_m|\mathcal{X}_{m_{\text{fake}}})$ so that the second term in the equation can also be suppressed in value.

**D. Discriminator**

For the $\mathcal{D}$ model of EVAGAN, we have separated the majority and minority class estimations using two different sigmoid ($\sigma$) functions as demonstrated in Figure 3. The benefit of separating the majority and minority class estimations is that we can feedback only minority class estimation to the $\mathcal{G}$. The other advantage of this structure is that we can separately calculate the estimation of both classes on test datasets to compare it with the ACGAN model later done in section V. The objective function of $\mathcal{D}$ has three parts as given by the Equations 10, 11 and 12. For the minority class terminologies, we use ’$m$’, and for the majority class, we use ’$M$’ in the following equations.

$$L_M = \mathbb{E}_{c_M \sim \mathcal{X}_{m \text{real}}} [\log P(C = c_M|\mathcal{X}_{m\text{real}})]$$  \hspace{1cm} (10)$$

$$L_{S_m} = \mathbb{E}_{y_m\sim \mathcal{X}_{m\text{real}}} [\log P(S = \text{real}|\mathcal{X}_{m\text{real}})] + \mathbb{E}_{y_m\sim \mathcal{X}_{m\text{fake}}} [\log P(S = \text{fake}|\mathcal{X}_{m\text{fake}})]$$  \hspace{1cm} (11)$$

$$L_m = \mathbb{E}_{c_m \sim \mathcal{X}_{m\text{real}}} [\log P(C = c_m|\mathcal{X}_{m\text{real}})] + \mathbb{E}_{c_m \sim \mathcal{X}_{m\text{fake}}} [\log P(C = c_m|\mathcal{X}_{m\text{fake}})]$$  \hspace{1cm} (12)$$

Hence, the objective function of the $\mathcal{D}$ can be represented as the sum of the three log-likelihoods to be maximized by the $\mathcal{D}$ as given by Equation 13

$$L^D(\mathcal{D}) = \text{argmax}(L_M + L_{S_m} + L_m)$$  \hspace{1cm} (13)$$

The first goal of the $\mathcal{D}$ is to correctly estimate the majority class distribution from the real samples only as $\mathcal{G}$ does not generate the majority class samples. Equation 10 denotes the log-likelihood for the real majority class samples. Equation 11 represents the source log-likelihood for the real and fake minority class samples. Equation 12 summarises the real and fake log-likelihoods from the $\mathcal{D}$ for minority class samples.
representativeness is the ability to reflect the real environment, which a botnet detector would need in deployment. Only Virut botnet was selected for this work because it had fewer samples as compared to other botnets except for Zeus, which had insufficiently low samples. The labels of SMTP or NSIS were not available on the website\(^2\). Hence, we used a subset with all the normal traffic flows and Virut samples. In this way, we could use this dataset as a good example of an unbalanced set. The distribution of the normal and Virut samples has been shown in Table I.

2) CIC-IDS2017 Dataset: The botnet chosen for the CIC-IDS2017 was Ares. For this bot, the traffic was collected on Friday, July 7, 2017, during the day from 10:02 AM – 11:02 AM in the CIC facility. The dataset is available on the CIC website\(^3\). Similar to ISCX-2014, a subset of this dataset using all the normal flows with botnet was created. The ratio of the number of samples has been mentioned in Table I.

3) CIC-IDS2018 Dataset: To create another subset of an unbalanced dataset of the botnet, we used CIC-IDS2018. This dataset included samples for Ares and Zeus botnets. We created a subset of all the normal and 2560 botnet traffic flows to generate another unbalanced dataset.

Table I
**Distribution of normal and botnet samples in cybersecurity botnet datasets**

| Dataset       | Normal | Real_bots | Total Samples |
|---------------|--------|-----------|----------------|
| ISCX-2014     | 246929 | Virut: 1748 | 248677         |
| CIC-IDS2017   | 70374  | Ares: 1956 | 72330          |
| CIC-IDS2018   | 590961 | Ares/Zeus:2560 | 393521 |

4) Feature Selection: The quality of a botnet dataset determines the performance of the botnet detectors in general and the number of distinct features in particular. A reduced feature set may not perform a stronger classification as compared to an enhanced set of non-redundant features [6]. In [25], authors summarised the most important network flow features that could be helpful in botnet detection. We have used almost all of these features, which were mentioned in [29] as well. The CICFlowMeter-v4 utility was used to extract 80 flow and time-based features\(^4\) from their .pcap files. This utility can be advantageous to extract the mentioned features for any input .pcap file.

5) Preprocessing: The ISCX-2014 dataset has not been labelled to be used in ML-based experiments. We used the information provided on the CIC website for IPs associated with the particular botnets to label the dataset. After labelling, we performed preprocessing as per Algorithm 1. All the high and low skewed values were removed to suppress outliers. The columns with NaN, Inf and zero standard deviation were removed. Finally, the data was scaled to the [0,1] range for the sake of using rectified linear unit (relu) activation function in the GAN model for data generation. The CIC-IDS2017 and CIC-IDS2018 were already labelled, so we only did preprocessing for these two datasets after extracting the unbalanced subsets. In our experiments, we used 70% of the cybersecurity subsets as training sets, and the rest of the 30% was used for testing the models and ML classifiers.

**Algorithm 1: Preprocessing**

**Input:** $X$ (original train set in csv format)  
**Output:** $T$ (preprocessed train set in csv format)

**begin**
\[
X_{normal} \leftarrow X[Label = 1], X_{botnet} \leftarrow X[Label = 0]; \quad // \text{label flows based on malicious IPs.}
\]

**Preprocess Data:** \quad // remove: outliers, rows with NaN and Inf values, columns with std=0 and scale the features in range\((0,1)\)

**D. CV Dataset**

1) MNIST Dataset: The MNIST dataset is a simplified collection of handwritten digits ranging 0 to 9 for training and testing various ML algorithms [30]. The purpose of using this dataset was to evaluate the performance of EVAGAN against ACGAN in terms of the visual quality of the images generated in balanced and unbalanced scenarios.

**E. Model Comparison of EVAGAN with ACGAN**

For the sake of comparison, we constructed four different variants of GANs, respectively ACGAN\(_CC\), EVAGAN\(_CC\), ACGAN\(_CV\), and EVAGAN\(_CV\). ACGAN\(_CC\) and EVAGAN\(_CC\) were trained and tested on CC datasets, and ACGAN\(_CV\), and EVAGAN\(_CV\) used CV datasets. The implementation details of each version in terms of hyperparameters can be found in Table II.

1) ACGAN\(_CC\) & EVAGAN\(_CC\): The structure of ACGAN\(_CC\) and EVAGAN\(_CC\) was made up of densely connected feed-forward neural network (FFNN) for both $G$ and $D$. The activation functions in hidden layers for both GANs were rectified linear units (relu). The hidden layers were regularized using batch normalization, and the optimizer type was Adam with binary cross-entropy (BCE). The difference between ACGAN\(_CC\) and EVAGAN\(_CC\) is in the output layers of $D$. The $D$ of ACGAN\(_CC\) outputs two neurons, one for the source probability and the other for the class probability for two classes (normal and botnet). The activation function is sigmoid for both outputs. The output layer structure of EVAGAN\(_CC\) has three neurons, one for the normal class, the second for the source probability, and the third is for the botnet class (minority class). Each of the three outputs leverages sigmoid as the activation function.

2) ACGAN\(_CV\) & EVAGAN\(_CV\): The CV based GAN architecture is different as it deals with image data in contrast to tabular data like that of CC. We need to use the convolutional neural network (CNN) instead of FFNN with other layers specific for image generation or detection. The output layer of $D$ is similar to CC based GAN implementations, except

\[^2\text{https://www.unb.ca/cic/datasets/botnet.html}
\[^3\text{https://www.unb.ca/cic/datasets/ids-2017.html}
\[^4\text{https://www.unb.ca/cic/datasets/ids-2018.html}\]
the Adam optimizer’s loss function has BCE for source estimations and sparse categorical cross-entropy (SCCE) for class labels. Here, BCE could have been used; however, to maintain the integrity of the original ACGAN, minimal changes to the code were made. However, in ACGAN_CC, we have used BCE as we converted the CNN based code to FFNN ourselves. In this way, we could keep ACGAN_CC and EVAGAN_CC as similar as possible for a fair comparison.

V. RESULTS

This section shows the results of the GAN implementations around two types of datasets: CC and CV GANs.

A. CC GANs

The results for quantitative analysis of the D’s performance on generated samples validity (GEN_VALIDITY), fake/generated botnet samples evasion (FAKE_BOT_EVA), real normal/majority class estimation (REAL_NORMAL_EST) and real botnet/minority class evasion (REAL_BOT_EVA) have been demonstrated in Figure 4. The ML classifier results have also been shown in this figure for the three CC datasets for comparison. Equations from 15-18 represent the mathematical expressions for these performance indicators. We have used Keras model.predict function to compute the values where the model is D as our prime objective is to devise an intelligent evasion aware classifier. Following is a brief detail of each evaluation parameter.

1) GEN_VALIDITY: In Equation 15, \( \hat{G}(z,c_m)[0] \) denotes the predicted value for the sources being fake or real. The Keras model.predict function outputs an array, so the average of the first elements in the array will be the source validity of the generated samples after every epoch. The more this value is close to ‘1’, the more it will be regarded as real.

\[
GEN\_VALIDITY = \frac{\sum[\hat{G}(z,c_m)[0]]}{N}
\]  

(15)

2) FAKE_BOT_EVA: In Equation 16, \( \hat{G}(z,c_m)[1] \) represents the probability estimation of generated minorit/botnet class samples. Since the label for minority/botnet class is ‘0’ so ideally, we expect from the model to output value close to ‘0’. We represent this estimation as the evasion of the generated samples. So the more this value is close to ‘0’, the less will be the evasion. Note that this is the second value in the sum of the model.predict function output.

\[
FAKE\_BOT\_EVA = \frac{\sum[\hat{G}(z,c_m)[1]]}{N}
\]  

(16)

3) REAL_NORMAL_EST: In Equation 17, \( \hat{X}_{normal, test}[2] \) represents the probability estimation of majority/normal class samples. Since the label for majority/normal class is ‘1’, ideally, we expect from the model to output the value close to ‘1’. Note that this is the third value in the sum of the model.predict function output for the normal samples from the test set.

\[
REAL\_NORMAL\_EST = \frac{\sum[\hat{X}_{normal, test}[2]]}{N}
\]  

(17)

4) REAL_BOT_EVA: In Equation 18, \( \hat{X}_{botnet, test}[1] \) represents the probability estimation of the real minority/botnet class samples. Our expectation from the model is to output the value close to ‘0’ similar to FAKE_BOT_EVA. This is the second value in the sum of the model.predict function output for the botnet samples from the test set.

\[
REAL\_BOT\_EVA = \frac{\sum[\hat{X}_{botnet, test}[1]]}{N}
\]  

(18)

5) Losses: The losses of D for real and fake minority classes, and majority/normal class, and the loss of G have been demonstrated in Figure 5 for both ACGAN and EVAGAN.

B. CV GANs

For ACGAN_CV and EVAGAN_CV, we use MNIST handwritten digits dataset. Only two classes of digits, ‘0’ and ‘1’,
were used in ACGAN_CV, as due to SCCE, its model does not accept fewer than two classes. For ECAGAN_CV, we use only the ‘0’ digit as the minority class. Since the MNIST data is already balanced, so to demonstrate the difference of performance, we need to undersample the values of the ‘0’ digit class. Four different undersampling levels have been devised in section VI. The evaluation parameters were equivalent to those used in CC GANs. For instance, GEN_VALIDITY is the same as GEN_VALIDITY. GEN_Eva is similar to FAKE_BOT_EVA but with minority class from MNIST, i.e. ‘0’ in our case. Similarly, ONE_Est is equivalent to REAL_NORMAL_EST, and ZERO_Eva is comparable to REAL_BOT_EVA in CC GANs. Figure 6 demonstrates the quantitative results for the four undersampling scenarios. Note that out of four, the first scenario exhibits 0% undersampling. That being said, there are actually three scenarios with undersampling, respectively, 50%, 90% and 99%. For qualitative analysis, the output from $\mathcal{G}$ of both ACGAN_CV and EVAGAN_CV has been demonstrated in Figures 8 and 9. These results are also based on the undersampling cases.

VI. Discussion

A. Detection Performance

If we analyze the results in Figure 4 for the first row that represents the ACGAN_CC results, we come to the understanding that the values for the REAL_NORMAL_EST and REAL_BOT_EVA remain close to each other. This implies that the $D$ of ACGAN_CC is not able to discriminate between the majority and minority class well due to the imbalance problem in all the three CC datasets. The $D$ of ACGAN_CC remains confused for the two classes in ISCX-2014 and CIC-2017 datasets. For the majority class, ACGAN_CC performs equally well as EVAGAN_CC for CIC-2018. However, for the minority class, due to the insufficient number of samples, it regards those as majority class samples. The second row in Figure 4 shows the results of EVAGAN_CC for the estimations on the test set. It can be observed that as compared to ACGAN_CC’s, the $D$ of EVAGAN_CC perfectly differentiates between the majority and minority classes and, after each epoch, tends to improve its detection performance for all the three CC datasets.

We have used FAKE_BOT_EVA as an indicator of evasion awareness of the $D$ in the case of EVAGAN_CC only because ACGAN_CC generates two classes of data so the $\mathcal{G}$ of ACGAN_CC would generate a random number of samples from both classes leading to non-deterministic values of FAKE_BOT_EVA. However, we compare the performance of this metric with ML classifiers. The last row of Figure 4 shows the results of the six different ML classifiers for the values of the majority, minority and generated class samples. It can be inferred that after a certain number of epochs, EVAGAN_CC tends to outperform the ML classifiers for all three values. The ML classifiers for black-box testing perform worst in the case of FAKE_BOT_EVA as compared to EVAGAN_CC for all the three CC datasets. This implies that the $D$ of EVAGAN_CC is not only adept at discriminating between real minority samples but can also easily detect the fake minority samples that ML classifiers are not good at. Another significant advantage of this $D$ is that we do not need to employ ML classifiers in CC for learning adversarial evasion. To make them adversarially aware, researchers use GANs to generate adversarial samples to be augmented with the training set for retraining ML classifiers. In the case of EVAGAN_CC, we save that time as the $D$ classifier/detector model is trained alongside the GAN training.

It can be illustrated from Figure 4 that the value of GEN_VALIDITY in the case of ACGAN_CC seems to remain close to 0.5 for all the three CC datasets. It means that the $D$ is confused in deciding whether the generated samples from $\mathcal{G}$ are real or fake. However, in the case of EVAGAN_CC, for all the three datasets, $\mathcal{G}$’s performance is improving with each epoch. This implies that $D$ is being fooled and still learning, while in the case of ACGAN_CC, the $D$ has already been saturated because $\mathcal{G}$ is not generating new samples that can fool $D$.

1) CV GANs: Figure 6 demonstrated the results of different undersampling scenarios to mimic the low data regimes for the MNIST dataset. Note that the detection performance of the $D$ for both ACGAN_CV and EVAGAN_CV for the majority and minority classes remains ideal from the very start. This is due to the reason that, unlike CC datasets, the CV dataset has many strong features due to which $D$ is easily able to differentiate between the ‘0’ digit and ‘1’ digit samples. However, the
The effect of undersampling can be seen for the minority class or digit '0' data. In contrast, the $D$ of EVAGAN.CV seems to be smart enough to give the steady values for all the undersampling cases, especially for minority class evasion (as depicted in red colour lines). Due to the sufficient number of samples, the majority class should be detected easily by both GANs, but in the case of 99% undersampling, ACGAN.CV exhibits a poor performance even detecting this class. For $G_{Validity}$, represented by the blue lines evidently show that in undersampling cases, the performance of $G$ of ACGAN.CV deteriorates in the worst manner and does not show any useful pattern of learning. This implies that in low data regimes, $G$ is not performing any better as compared to EVAGAN.CV. However, EVAGAN.CV also shows the deterioration in $G$’s performance, but that is not as phenomenal as that of ACGAN.CV.

B. Stability

The Figure 5 shows the $D$ and $G$ losses for CC GANs. It can be inferred from this diagram that the values for all the losses seem to be converging. This shows that the GANs are saturating towards Nash equilibrium. However, in the case of EVAGAN_CC, the losses tend to be more steady with each epoch and achieve the lowest point sooner as compared to ACGAN_CC. Similarly, for CV GANs, the EVAGAN.CV losses in all the undersampling cases tend to be more stable as compared to ACGAN.CV as demonstrated in Figure 7.

C. Qualitative Performance

It is non-trivial to demonstrate the performance of a GAN in the case of CC datasets [31]. Since we can not visualize the generated network traffic, so we need to validate the EVAGAN with the help of CV datasets. The rationale for using CV datasets is that if EVAGAN outperforms ACGAN in unbalanced scenarios, then it would be equally acceptable for CC datasets. Since our purpose is not to generate quality traffic for CC, rather, we need to design an evasion aware anomaly detector. So, evaluating EVAGAN_CC for quality traffic generation is not in the scope of this work.

The previously mentioned undersampling scenarios for CV GANs have been demonstrated in Figures 8 and 9. There are two $15 \times 10$ matrices of pictures in each figure. The
number of images in each matrix is equal to the total number of epochs, i.e. 150. In each figure, the upper row belongs to the ACGAN_CV output of the $G$ and the lower row corresponds to the output from $G$ of EVAGAN_CV. Note that for ACGAN_CV, there are two classes being output from $G$ and for EVAGAN_CV, only one ‘0’ digit class is generated. For the undersampling scenario in which contain 50% fewer ‘0’ class samples, the deterioration for ACGAN_CV starts getting evident, but EVAGAN_CV is able to generate ‘0’ digits. For the case of 90% undersampling, the ACGAN_CV quality miserably deteriorates; however, EVAGAN_CV is still generating the ‘0’ class samples although slightly faded. In the 99% undersampling case, as expected, the ACGAN_CV is still struggling to generate the minority class digit ‘0’, but an interesting case has happened for EVAGAN_CV. Since the number of samples is minuscule so the feedback taken from the $D$ by $G$, on some accidentally generated ‘1’ digit, gave a small value of $G_{Loss}$. Due to this reason, the $G$ started generating the majority class ‘1’ digit after epoch 47. This situation is called a mode collapse which is an inherent problem in GANs. However, we can infer that EVAGAN_CV may not perform well in a highly unbalanced scenario. This is an interesting research direction to further investigate using other CV datasets as well. On the other hand, ACGAN_CV is also stuck in mode collapse after epoch 140, where in place of ‘0’ class ‘1’ class samples start appearing. However, in the case of EVAGAN_CV, despite mode collapse, the generated samples from class ‘1’ are of higher quality which means that
its $G$ is more powerful as compared to that of ACGAN in highly unbalanced scenarios.

### D. Time Complexity

The time complexity bar chart has been demonstrated in Figure 10 where y-axis represents the values of the training time in minutes. The MNIST dataset case with no undersampling was used to compare the results. The time complexity may vary on different platforms (for instance, Google Colab); however, the plot in Figure 10 shows the results on the workstation that we have used. It can be observed that EVAGAN always takes less time than its counterpart for all four datasets. The reason lies in the notion that the $G$ of EVAGAN in the cases of all the datasets needs to follow lesser diversity as compared to ACGAN. Although the batch size of 256 (given in Table II) is the same for both GANs, the amount of time taken by EVAGAN is always less. Due to the stochastic nature of the input noise $z$ for the $G$, we cannot estimate the exact time in minutes for every training cycle; however, the average time of EVAGAN always remains less as compared to ACGAN.

A question might arise why we did not make ACGAN generate only the minority class samples. The answer to this question is that we would have to make changes in the structure of both $G$ and $D$ along with the loss functions. The SCCE loss does not allow us to use less than two classes, so we need to use BCE loss with other structural modifications. EVAGAN is the name of this transformation.

### VII. CONCLUSION

Adversarial evasion attacks on AI-based systems are a portending threat that needs to be dealt with using intuitive methods. Adversarial learning is one of the modern techniques to make ML classifiers proactively adept at detecting the adversarial evasion samples. In this paper, we have proposed a novel GAN model called EVAGAN that generates adversarial evasions in low data regimes. EVAGAN is an enhancement of a well-known model called ACGAN. The purpose of EVAGAN is to design an adversarial aware classifier for anomaly detection. We have used two types of datasets; one from the cybersecurity domain for botnets and the other from the computer vision called MNIST. EVAGAN’s discriminator proves to be superior to ACGAN in terms of detection performance, stability, and time complexity. At the same time, the qualitative analysis shows that EVAGAN outperforms ACGAN in unbalanced scenarios. EVAGAN model has been designed for binary classification problems. Further investigation for multiclass design is a potential research direction. Experiments with other datasets would be highly desirable to further evaluate EVAGAN for the said parameters. For the qualitative analysis, the handwritten digits other than ‘0’ and ‘1’ could be used to further validate EVAGAN’s superiority over ACGAN. A comparison with few-shot learning could be an interesting research direction.

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