Generating Adversarial Inputs Using A Black-box Differential Technique

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Neural Networks (NNs) are known to be vulnerable to adversarial attacks. A malicious agent initiates these attacks by perturbing an input into another one such that the two inputs are classified differently by the NN. In this paper, we consider a special class of adversarial examples, which can exhibit not only the weakness of NN models—as do for the typical adversarial examples—but also the different behavior between two NN models. We call them difference-inducing adversarial examples or DIAEs. Specifically, we propose DAEGEN, the first black-box differential technique for adversarial input generation. DAEGEN takes as input two NN models of the same classification problem and reports on output an adversarial example. The obtained adversarial example is a DIAE, so that it represents a point-wise difference in the input space between the two NN models. Algorithmically, DAEGEN uses a local search-based optimization algorithm to find DIAEs by iteratively perturbing an input to maximize the difference of two models on predicting the input. We conduct experiments on a spectrum of benchmark datasets (e.g., MNIST, ImageNet, and Driving) and NN models (e.g., LeNet, ResNet, Dave, and VGG). Experimental results are promising. First, we compare DAEGEN with two existing white-box differential techniques (DeepXplore and DLFuzz) and find that under the same setting, DAEGEN is 1) effective, i.e., it is the only technique that succeeds in generating attacks in all cases, 2) precise, i.e., the adversarial attacks are very likely to fool machines and humans, and 3) efficient, i.e., it requires a reasonable number of classification queries. Second, we compare DAEGEN with state-of-the-art black-box adversarial attack methods (Simba and Tremba), by adapting them to work on a differential setting. The experimental results show that DAEGEN performs better than both of them.

1 INTRODUCTION

In 2016, a Tesla vehicle, driving in autopilot mode, crashed against a white truck after it failed to identify the truck as an obstacle (Vlasic and Boudette [2016]). Further investigation revealed that the autopilot system misclassified the truck as a bright sky. The Tesla driver died in the crash. In 2018, a pedestrian was struck and killed by an Uber test vehicle after it failed to recognize the obstacle as a human (Lubben [2018]). These are examples that illustrate the importance of properly testing the software that controls these vehicles.

Neural networks (NNs) are computing systems capable of learning tasks from examples. NNs is the technology used to control the vehicles mentioned above. They have been recently applied in various domains, including image classification (Guo et al. [2017]), malware detection (Yeo et al. [2018]), speech recognition (Juang et al. [2007]), medicine (Sengupta et al. [2016]), and vehicle control and trajectory prediction (Zissis et al. [2015]). NNs are known to be vulnerable to adversarial attacks (Goodfellow et al. [2014b], Papernot et al. [2017], Szegedy et al. [2013]). A malicious agent creates these attacks by finding a pair of similar inputs—typically, indistinguishable by the human eye—where the NN produces different outputs, one of which is incorrect. With that knowledge, a malicious attacker can exploit neural-network-bearing systems to perpetrate illicit acts. Adversarial attacks pose a significant threat to the reliability of machine learning systems today. The Tesla and Uber accidents could have been prevented had the autonomous

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vehicles been tested against adversarial attacks. There exists intensive research on adversarial attacks and defences today (See Chakraborty et al. [2018] and Huang et al. [2018] for recent surveys).

**DIAEs.** This paper focuses on a particular class of adversarial examples that can differentiate two NN models trained on the same dataset. As Pei et al. [2017] we use the term DIAE (for Difference-Inducing Adversarial Examples) to refer to this class of inputs. The study of the differential behaviour between two NN models has been motivated by the current debate between the transferability of adversarial examples (Papernot et al. [2017]) and the fact that decision boundaries of two models can be drastically different even if they are trained on the same dataset (Liu et al. [2017]). Because the adversarial examples lie at decision boundaries, the difference on decision boundaries suggests the non-transferability of adversarial examples. In this paper, instead of directly participating on this debate, we provide a technique and corresponding tool to identify DIAEs, i.e., those adversarial examples that perform differently on the two models. The discovery of a DIAE suggests a point-wise failure of transferability and a point-wise difference in the decision boundaries of two NN models.

**Black-box Attacks.** White-box techniques exist to generate DIAEs (Pei et al. [2017]). We are interested in black-box methods for its practicality. Black-box methods rely only on the input and outputs of the NNs to produce adversarial examples. They do not need access to the gradients of a NN, which is the key ingredient used in white-box attacks, including the most successful ones, such as C&W attack (Carlini and Wagner [2017]). In simple words, we run both techniques on a single target NN, saving the adversarial inputs they generate. Then, we later select a second NN model and check if the outputs of this model match the outputs of the target model on these adversarial inputs. We consider the number of mismatches to be the number of difference inducing inputs.

**Solution.** This paper proposes DAEGEN, a lightweight black-box technique that leverages the diversity of different NNs to generate adversarial attacks. DAEGEN is the first black-box technique to use Differential Testing (McKeeman [1998]) to find DIAEs. For a given seed input \( x \), DAEGEN searches for adversarial inputs \( x' \) that maximize the distance between the outputs that the two models produce to \( x' \) (as to fool machines) while minimizing the distance between \( x \) and \( x' \) (as to fool humans). We conjecture that the combination of these goals enables DAEGEN to produce high-quality adversarial inputs efficiently. Although differential testing has been used in testing of NNs, specifically DeepXplore (Pei et al. [2019]) and DLFuzz (Guo et al. [2018]), both of them are white-box. In addition, there are significant technical differences between DAEGEN and these two methods. Unlike DAEGEN which finds DIAEs by minimising the difference between predictive confidences of two NN models, DeepXplore focuses on neuron coverage—a metric of test adequacy—and is designed to find DIAEs by ensuring that more neurons in one of the models are activated. In other words, DeepXplore does not aim at exploring the different behavior between NN models—it explores the difference between models to study adversarial behavior in one of the models. In contrast, DLFuzz takes a single model on input instead of more than one, as DeepXplore and DAEGEN do. DLFuzz is not designed to work with DIAEs.

**Summary of Evaluation.** We conducted an extensive set of experiments to validate the performance of DAEGEN by comparing it with state-of-the-art white-box (differential) techniques and black-box (non-differential) techniques. A simple adaptation (details explained in Section 5) is needed to make those non-differential techniques work on our differential setting. For white-box techniques, we compared DAEGEN against DeepXplore (Pei et al. [2019]) and DLFuzz (Guo et al. [2018]). For black-box techniques, we compared DAEGEN against Simba (Guo et al. [2019]) and Tremba (Huang and Zhang [2020]). We analyzed these techniques on three orthogonal dimensions: 1) effectiveness, 2) precision, and 3) efficiency. Effectiveness refers to the number of times a technique was successful in generating DIAEs. Precision refers to the quality of the adversarial inputs generated. Intuitively, more similar inputs are preferable as they are more difficult to catch by the human eye. Efficiency refers to the computation cost of the technique. We
used three popular image datasets in the evaluation, namely, MNIST (Lecun et al. [1998]), ImageNet (Deng et al. [2009]), and Driving (udacity challenge [2016]) and several NN models frequently used in the evaluation of related techniques.

Summary of Results. Considering the comparison with white-box techniques, DAEGEN was the only technique capable of generating adversarial examples in all cases and it was the fastest technique. Considering the comparison with black-box techniques, DAEGEN was able to produce DIAEs in 99.2% of the cases whereas Simba and Tremba produced DIAEs on rates of 73.1% and 76.9%, respectively. Furthermore, DAEGEN produced images with much lower $L_2$ values (i.e., Euclidean distance of the generated input to the seed image) than Tremba and slightly higher $L_2$ values than Simba. Overall, these results provide initial, yet strong evidence that our approach is effective to produce difference-inducing inputs at higher rates.

This paper makes the following original contributions:

- **Technique.** DAEGEN, the first black-box technique for finding DIAEs;
- **Tool.** A publicly available tool implementing DAEGEN;
- **Evaluation.** A comprehensive evaluation of DAEGEN including a variety of white- and black-box techniques, datasets, and NN models. Experimental results indicate that DAEGEN is effective, precise, and efficient. Evaluation artifacts are publicly available at the following link https://github.com/daegen/DaegenAttack.

## 2 EXAMPLE

Consider that a manufacturer of an autonomous vehicle wants to test the robustness of the NN models before they are deployed on their vehicles. The focus is on a specific NN that outputs a correction angle on the steering wheel based on what it observes from the pictures that the front camera of the vehicle takes. For example, the NN would instruct the vehicle to adjust the steering wheel’s angle to prevent the vehicle from falling off an approaching cliff. Other nets on the vehicle could be used to monitor other environmental signals and to take other actions (e.g., whether or not to slow down or stop). This example focuses on driving direction.

DAEGEN is a technique to test the robustness of an NN. It takes as input a seed object (e.g. an image) and two NN models—the testing target and the surrogate model for the target. As a black-box technique, DAEGEN uses information on the input and output of the net to search for examples. There are multiple ways to obtain surrogate models. First, as shown by Papernot et al. [2016], a surrogate model can be created from scratch, by training over a set of training data sampled from the model to be tested. Second, in some application domains, surrogate models may be available off-the-shelf. For example, on benchmark datasets such as ImageNet, there exist many well-trained models publicly available. The second way is becoming a trend in self-driving applications, with more and more benchmark datasets released (e.g., Waymo’s Open Dataset (Waymo [2020])).

Figure 1 shows an example of an adversarial input produced by DAEGEN. The seed (original) input to test the NN appears on the left-hand side of the figure. Note from the numbers below the image on the left that both the tested net (NN1) and the surrogate net (NN2) produce a similar response to this input—a .19 degree to the right (as the angle is positive). The angles are not identical; we only showed two decimals in the figure for space. The right side of the figure illustrates a very similar, but not identical, image for which the tested network and the surrogate network differ, by a considerable amount, on the result they produce. The network NN1 instructs the vehicle to go almost straight, whereas the NN2 instructs the vehicle to steer to the right. Regardless of which network is incorrect, there exists a problem.

We remark that our focus is not on the differential behavior of the NN models on the original input, as studied by Adamu et al. [2015], Johansson et al. [2007]. Instead, we study the different behavior of the NN models on the
perturbed inputs, as shown in the right-hand side of Figure 1. Our focus is on the different robustness capability of the models and on identifying such adversarial inputs. A DIAE shows a difference in the robustness capability of two nets. Unlike general adversarial examples, whose actual safety risk is arguable (Ilyas et al. [2019], Lu et al. [2017]), DIAEs, which are special kinds of adversarial examples, represent an actual risk because they show a concrete manifestation of disagreement between two models.

DAEGEN uses a classical Hill-Climbing search (Russell and Norvig [2009]) to produce adversarial examples. It 1) randomly selects a pixel from the image, 2) makes random perturbations on that pixel, 3) queries the models and measures fitness of the new image, and 4) stops if a sufficiently good adversarial input (according to fitness value) has been produced or it reached a budget on the number of queries to the models. Otherwise, if there was no fitness improvement, DAEGEN continues execution on step 1 with the image it initiated the current iteration. If there was fitness improvement, it continues execution on step 1 with the image modified in the current iteration.

The sensible part of DAEGEN is the objective function it uses to search for examples. As a black-box technique, DAEGEN only uses information available on the input and outputs. The objective function expresses two primary goals: 1) to maximize the distance between the outputs produced by the test and the surrogate networks (0.21 in the adversarial example above) and 2) to minimize the distance between the inputs. DAEGEN uses the Euclidean distance between two images to that end. The rationale is that these two goals reflect the intention of an adversarial attack—to fool machines (as per the first goal) and humans (as per the second goal).

3 PRELIMINARIES
This section introduces fundamental concepts and terminology used in the paper.

Adversarial attacks apply input generation methods to exploit NNs (Serban and Poll [2018], Yuan et al. [2017]). Given an input $x$, the attacker goal is to look for another input $x'$ such that one of the following objectives is satisfied: confidence reduction (i.e., the confidence of classifying $x'$ as a given label is reduced to a certain level), non-targeted misclassification (i.e., $x'$ is classified into any other label that is different from $x$), and targeted misclassification (i.e.,
$x'$ is classified into a given label that is different from $x$). Non-targeted and targeted attacks are specialized forms of confidence reduction attacks. This paper focuses on non-targeted attacks.

Attack methods differ in how much access they have on the NN. Attacks can be white-box or black-box. A white-box attacker has unlimited access to the NN. For example, the attacker knows the hyper-parameters, architecture, model weights, data used to train the network model, and defense methods. Hence, the attacker can replicate the model under attack. In particular, a white-box attacker can compute the gradient of loss for an input. The FGSM attack (Szegedy et al. [2013]), for instance, leverages that information. In contrast, black-box attacks have limited access to the NN. For a given input $x$, the attacker will only know the distribution of the output or partial information about the output distribution, as discussed below. This paper proposes a black-box attack method.

While white-box attack are appealing and many attack methods use the gradients of a network, black-box attacks have a practical edge. Existing literature describes three characteristics of black-box attacks (Ilyas et al. [2018]). The first one is limited query, where the attacker may, for example, be limited to a small number of queries. Many commercial or proprietary systems may limit the ability of the attacker to access its classifiers. This characteristic highlights the importance of query efficiency in black-box attacks, thereby setting the ground for using the number of queries as a metric of performance of the attack methods (see Section 5.1). The second characteristic is partial information. Attackers may have access to only the top-$k$ class probabilities when querying the model, instead of the probability distribution of all classes. DAEGEN works with partial information; it only uses the top class from the probability distribution. Finally, the third characteristic is label only, where the attackers cannot access the probability distributions. Instead, the only information available is the top-$k$ inferred labels. DAEGEN does not work with this characteristic as it needs both the top-1 label and its probability.

3.1 Black-box attack formulation

We formally describe a black-box adversarial attack in the following. Consider that a NN model $S$ is trained to classify images into a set of $k$ classes (i.e., labels). $S$ can be formalized as a function:

$$f : \mathbb{R}^d \rightarrow [0, 1]^k,$$

where $d$ is the number of input features. The output of function $f$ is a probability distribution, representing the probability of $S$ classifying the input $x$ into any of the $k$ labels. Formally, when $S$ is queried with the input image $x$, it responds by returning a tuple containing, for example, label $y \in 0...k$ and a probability $P(y|x) \in 0..1$. Non-targeted misclassification can be formulated as an optimization problem (Pei et al. [2019]), as follows:

$$\min_{x' \in \mathbb{R}^d} \|x - x'\|_2 \text{ s.t. } \arg \max_{t \in 1...k} f(x) = \arg \max_{t \in 1...k} f(x') \quad (1)$$

The goal is to find an adversarial image $x'$, where the difference between $x$ and $x'$ is minimized when the label changes. Perturbation norms are used to define the acceptable distance between original and perturbed images (Bhambri et al. [2019]). Specifically, the expression $\|x - x'\|_2$ denotes the $L_2$ (Euclidean) distance between the inputs $x$ and $x'$. In addition to $L_2$, $L_1$ and $L_\infty$ are also commonly used. The right side of the equation expresses the condition that the label needs to change for the attack to have an effect.
4 A BLACK-BOX DIFFERENTIAL APPROACH FOR ADVERSARIAL INPUT GENERATION (DAEGEN)

This section describes DAEGEN, a black-box differential method to find adversarial inputs in NNs. Figure 2 summarizes the workflow of DAEGEN. DAEGEN uses search to identify adversarial inputs in NNs. However, in contrast to state-of-the-art white-box (differential) techniques, e.g., (Pei et al. [2019]) and (Guo et al. [2018]) and black-box (non-differential) techniques, e.g., (Guo et al. [2019]) and (Huang and Zhang [2020]), DAEGEN is inspired by the recent success of fuzzing (Godefroid [2020]), which is a highly effective, mostly automated, security testing technique. In particular, in evolutionary black-box fuzzing, if a mutation of the input triggers a new execution path through the code, then it is an exciting mutation; otherwise, the mutation is discarded. By producing random mutations of the input and observing their effect on code coverage, evolutionary black-box fuzzing can learn what interesting inputs are. Based on this observation, DAEGEN queries the NNs with given input and then makes perturbations (mutations) on the input based on observations obtained from the previous queries (learning). This process is repeated until finding an adversarial input or reaching a budget on the number of queries.

4.1 Attack formulation

Technically, DAEGEN systematically searches the input space to (i) maximize the output/output difference while (ii) minimizing the input/input difference. The output/output difference consists of the difference between the outputs produced by each NN. For example, for classification problems, NNs often reports probability distributions indicating the likelihood of the input belonging to a given class. In those cases, DAEGEN maximizes the difference between the two distributions reported. Simultaneously, DAEGEN minimizes the difference between the perturbed input and the original input.

Formally, given two functions $f_1$ and $f_2$ and an input $x$, the optimization problem can be described as:

$$\max_{x' \in \mathbb{R}^d} \| f_1(x') - f_2(x') \|_1 \quad \text{s.t.} \quad \| x - x' \|_p \leq \epsilon, \quad \arg \max f_1(x) \neq \arg \max f_2(x').$$

(2)

Intuitively, it is to find an adversarial example $x'$ that maximizes the difference between outputs from $f_1$ and $f_2$, such that $x'$ is not too far away from $x$, and there exists a misclassification.

Consider the example illustrated in Figure 1 and the formalization in Eq. (2). One could apply an optimization algorithm to randomly add noise patterns to the street road. This means that noises (or combinations of noises), which maximize the difference between the output of NN1 and the output of a NN2 for the perturbed street road, will be kept until the search algorithms find a feasible solution.
4.2 Hill Climbing (HC) optimization

In order to solve the optimization problem in Eq. (2), Hill Climbing (HC) (Russell and Norvig [2009]), a mathematical optimization technique suited for local search problems, is chosen. HC is an iterative algorithm that starts with an arbitrary solution for a given problem, and at each iteration, it adds incremental alterations to the solution. The core components of HC are described below:

- **Selection.** A new solution is generated by adding random mutation to a previously generated solution.
- **Evaluation.** The evaluation function calculates a score that measures the quality of a solution candidate.
- **Termination.** The algorithm terminates if the solution has converged, i.e., the algorithm is unable to produce new solutions that are different from the previous solution.

Algorithm 1: Hill Climbing algorithm for difference inducing adversarial examples generation.

**Data:** Input original example $x$; two target models $NN_1$ and $NN_2$ as black-box functions $f_1$ and $f_2$, respectively; maximum number of allowed iterations $T$; a constant $c$ to re-scale the $L_2$ value

**Result:** Output an adversarial example $x'$ if any, or the best solution it could find before termination.

```
Function Selection($x'$):
    pixelIndex ← rand(0, len($x'$))
    $x'$[pixelIndex] ← rand(0, 255)
    return $x'$

Function Evaluation($x'$):
    return $\Omega(x, x')$

sol ← Selection($x$)
score ← Evaluation($x$)
i ← 0
while ¬Termination(sol, i) do
    newSol ← Mutation(sol)
    newScore ← Evaluation(newSol)
    if newScore > score then
        sol ← newSol
        score ← newScore
    i ← i + 1
x' ← sol
```

In Algorithm 1, we present our implementation of the HC algorithm for DAEGEN attack. This algorithm receives as input four parameters as follows. a) $x$ is the original image. b) $y$ is the true label of $x$. c) $f_1$ and $f_2$ are two NN models $NN_1$ and $NN_2$. d) $T$ is the maximum number of iterations the algorithm is allowed to have. e) $c$ is a constant factor that we can use to re-scale the $L_2$ value, and it is used during the evaluation step (see, Eq. (3)). This is important because we need to make sure the $L_2$ and the score derived from the difference between the NN are on the same scale to avoid that algorithm gives too much importance to the perceptual aspect of our optimization (i.e., minimizing the difference between the images), ignoring the differential aspect. On the other hand, if we set $c = 0$ we can make the algorithm ignore the perceptual aspect of the optimization and focus only on maximizing the differential behavior of the NNs. The basic intuition behind this is that the algorithm can only succeed if it is able to find difference inducing solutions,
which is achieved by maximizing divergent behavior on the NN, while the $L_2$ forces the algorithm to find solutions that are closer to the original inputs. If that is not a need we can flex the importance of this aspect of the attacks. The mutation function is responsible for adding pixel-level noises/perturbations to a given image $x$; it randomly selects a single pixel from the image and modifies its original value by a new randomly generated value. A generated solution is then evaluated by calculating a score using Eq. (3).

$$\Omega(x, x') = \text{abs}(f_1(x') - f_2(x')) - c \cdot \text{norm}(x' - x)$$ (3)

5 EVALUATION
We organized the evaluation based on whether or not a technique leverages code of the NN to obtain adversarial inputs (i.e., white- versus black-box) and whether or not a technique takes multiple NN models on input (i.e., differential versus non-differential). Intuitively, our goal is to understand the impact of each of these aspects on the performance of an adversarial input generation technique.

We pose the following questions:

- **RQ1.** How DAEGEN compares with White-box Differential techniques? (Section 5.2)
- **RQ2.** How DAEGEN compares with Black-box Non-differential techniques? (Section 5.3)

We conducted all experiments on a machine with two Intel(R) Core(TM) i7-8750H CPU @ 2.20GHz processor, 2208 Mhz, 6 Core(s), 12 Logical Processor(s), 32 GB of DDR4 memory, NVIDIA GeForce GTX 1070 GPU. We used Python 3.5.6, PyTorch 1.0.1, Torchvision 0.2.23, Keras 2.0.8, Tensorflow 1.10.0 and Windows 10 Pro OS.

The tool implementing DAEGEN and the scripts to reproduce our experimental results are publicly available at the following link https://github.com/DAEGEN/DAEGENAttack.

5.1 Metrics
We evaluated techniques in three dimensions:

1. **effectiveness** determines how successful a technique is in generating adversarial examples;
2. **precision** determines the ability of generated examples to fool machines and humans;
3. **efficiency** determines how computationally efficient a technique is.

The following sections explain the metrics used to assess effectiveness, precision, and efficiency.

5.1.1 Effectiveness. We used the Differential Success Rate (DSR) as proxy for effectiveness. This metric measures the relative number of DIAEs (see Section 1), which a given technique produces on a pair of models. In the following, we define how we computed DSR for differential and non-differential techniques. These definitions differ because non-differential techniques take one NN model on input, in contrast with differential techniques, which take two. **DSR of Differential Techniques.** Let $M$ define the kind of a network model, and let $X$ define the set of inputs (e.g., the set of images). We define a differential technique as a function $t: M \times M \times X \rightarrow \mathbb{Z}_2 = \{0, 1\}$, where 1 indicates that the technique was successful in producing an adversarial example, while 0 indicates otherwise. That function takes two classification models in $M$ and seed in $X$ as input and produces an output indicating success or failure. In successful attacks, for any pairs of models $m_1, m_2 \in M$, the following proposition must hold $m_1(x) \neq m_2(x)$, for any seed input $x \in X$. The Differential Success Rate (DSR) of a differential technique $t$ is obtained by comparing the outputs of any two models $m_1, m_2 \in M$ on a given set of seed inputs $X_0 \subseteq X$. More formally, we define the DSR of a technique $t$
with respect to two models \( m_1 \) and \( m_2 \) and inputs \( X_0 \) as \( \text{DSR}(t, m_1, m_2, X_0) = \frac{1}{|X_0|} \times \sum_{x \in X_0} t(m_1, m_2, x) \). \( X_0 \), referred to as \( \text{DSR}(t, X_0) \), is obtained by computing the average \( \text{DSR} \) across all pairs of models in \( M \).

**DSR of Non-Differential Techniques.** We included non-differential techniques in the evaluation. Unfortunately, the \( \text{DSR} \) formulation above is inadequate for these techniques, as they take only one model on input. To circumvent that issue, we defined a differential technique \( p \), based on its non-differential technique \( t \), to decide if the adversarial input produced by \( t \) is a DIAE (see Section 1). Intuitively, \( p \) checks, for a given pair of models \( (a, b) \), whether or not the adversarial input produced by a (non-differential) technique for the model \( a \) results in a different output when fed to \( b \). The computation of \( \text{DSR} \) is as described for a differential technique.

### 5.1.2 Precision.

Given the impossibility to automatically quantify the ability of humans to perceive changes in a pair of images (Rony et al. [2018]), it is common practice to adopt metrics of image similarity as a proxy of perception. We used the Euclidean distance between two images – the \( L_2 \) norm – to quantify image similarity. This norm has been consistently used in prior related work.

### 5.1.3 Efficiency.

We used time and number of queries submitted to the models to measure efficiency, which has been shown to be important in some domains (Bhamini et al. [2019]).

### 5.2 White-box (Differential) Techniques

This section elaborates on the comparison of DAEGEN with white-box techniques.

#### 5.2.1 Comparison Techniques.

We selected two recently-proposed popular white-box differential techniques for comparison – DeepXplore (Pei et al. [2017]) and DLFuzz (Guo et al. [2018]). DeepXplore introduced the concept of neuron coverage criterion and was the first technique to use differential testing in this domain. It uses multiple (similar) \( \text{NN}s \) to find discrepancies in results. The approach exploits the differential behavior of a set of \( \text{NN}s \) to generate adversarial input images. The adversarial input generation problem is formalized as a joint optimization problem, where the following objectives are considered: 1) to maximize output divergence and 2) to maximize neuron coverage. A gradient ascent search strategy is used to create perturbations on inputs to maximize both objectives. We considered three configurations of DeepXplore for comparison: Light, Occl, and Blackout. Similar to DeepXplore, DLFuzz is also differential. However, DLFuzz does not require additional model(s) to find adversarial attacks. Instead of looking for inconsistent behavior across many \( \text{NN} \) models, it looks for inconsistent classification within a single \( \text{NN} \) model. The attack method assumes that the first classification given by the classifier for a given seed input is correct and takes it as ground truth. An adversarial attack is reported if the technique can produce similar inputs with different classification.

#### 5.2.2 Datasets and Models.

We used two image datasets in the evaluation: MNIST (Lecun et al. [1998]) and Driving (udacity challenge [2016]). MNIST is a dataset of handwritten digits, which contains 70K grayscale \( 28 \times 28 \) (in pixels) images, divided into ten classes, i.e., digits 0–9. Driving is a dataset made available by the Udacity self-driving car challenge. It contains 5,614 images captured by a self-driving car labeled with the steering wheel angle that should be applied by the driver at the time each image was captured.

Table 1 shows the datasets and models we used. We focused on datasets and models 1) used in the evaluation of both DeepXplore and DLFuzz and 2) used in the autonomous-vehicle domain.

#### 5.2.3 Setup.

We set a budget of 50K queries on DAEGEN to give it enough time to generate adversarial examples. Recall that DAEGEN stops when the first adversarial example is produced. In that case, the budget is not reached.
Table 1. Datasets and Models used for comparison of DAEGEN with White-Box techniques.

| Datasets    | Model (Source)        | Used at                        |
|-------------|-----------------------|--------------------------------|
| MNIST       | LeNet1 (Lecun et al. [1998]) |                                |
|             | LeNet4 (Lecun et al. [1998]) | Guo et al. [2018], Pei et al. [2017] |
|             | LeNet5 (Lecun et al. [1998]) |                                |
| Driving     | Dave-orig (Bojarski et al. [2016]) | Pei et al. [2017] |
|             | Dave-norminit (Simonyan and Zisserman [2014]) |                                |
|             | Dave-dropout (Simonyan and Zisserman [2014]) |                                |

Such a high number of queries enables us to understand the actual cost of DAEGEN better. DeepXplore and DLFuzz, unlike DAEGEN, can produce multiple adversarial examples for a given input. To fairly compare these techniques with DAEGEN, we recorded only the first adversarial example they generate for a given input seed. Note that number of attacks per input is irrelevant for DSR, which focuses on whether or not an attack was successful.

We followed usage instructions from DeepXplore [dxr, 2020] and DLFuzz [dlf, 2020]; we did not change any part of their code. DeepXplore and DLFuzz offer command-line parameters to stop when the first example is found. This methodology ensures that when any of these tools stop, they either succeed in generating adversarial inputs or fail due to their limitations.

5.2.4 Results. Table 2 summarizes the results of each technique. We grouped results by datasets (see Table 1). Recall that DLFuzz cannot handle the Driving dataset as is and we chose not to change the code (see Section 5.2.1). Observe that, for “DSR” (effectiveness), the higher the value the better, whereas for “Avg. $L_2$” (precision) and “Avg. Time (s)” (efficiency), the lower the value the better.

Table 2. Average results comparing DAEGEN and White-Box techniques: DeepXplore (three variants) (Pei et al. [2017]) and DLFuzz (Guo et al. [2018]).

| Dataset    | Technique   | DSR   | $L_2$   | Time (s) |
|------------|-------------|-------|---------|----------|
| MNIST      | DeepXplore light | 0.732 | 14.034  | 5.573    |
|            | DeepXplore occl  | 0.831 | 5.029   | 6.477    |
|            | DeepXplore blackout | 0.624 | 1.041   | 7.321    |
|            | DLFuzz        | 0.918 | 2.611   | 5.205    |
|            | DAEGEN        | 1.0   | 6.914   | 0.4      |
| Driving    | DeepXplore light | 0.366 | 90.055  | 11.006   |
|            | DeepXplore occl  | 0.927 | 60.680  | 8.683    |
|            | DeepXplore blackout | 0.070 | 25.765  | 9.271    |
|            | DAEGEN        | 1.0   | 7.082   | 4.939    |

Results indicate that the DeepXplore blackout combination was the one that performed best in the MNIST, where it produced examples with lower $L_2$. However, that combination failed to produce examples in several cases. Overall, DLFuzz performed well on the MNIST dataset since it produced adversarial examples in 91.8% of the cases, and the examples have relatively low $L_2$ values. Results show that DAEGEN generated adversarial examples in every case and that it was more efficient than every other technique. The average $L_2$ norm of (the examples produced by) DAEGEN is not always superior to other techniques’ $L_2$. For example, three techniques on the MNIST dataset produce examples with lower average $L_2$ than DAEGEN. The reason is that the setup we used for DAEGEN weighs efficiency (i.e., execution
time) higher than precision (i.e., \(L_2\)). In principle, all techniques could produce examples with lower \(L_2\) by executing each query until reaching execution bounds instead of stopping on the first adversarial example produced. However, that setup would lead to higher execution times, as we did. We elaborate and discuss the importance of \(L_2\) in the following.

**Effectiveness.** Table 3 shows the breakdown of DSR per NN model. The columns under “DSR” show the DSR of a technique for a given pair of the dataset (column “Dataset”) and model. Note that DeepXplore and DLFuzz perform relatively well when considering DSR alone. The highlighted cells show the best DSR obtained below 1.0. Overall, DLFuzz performed well on the MNIST dataset, whereas DeepXplore occl performed well on Driving. Recall that DAEGEN can produce adversarial examples in every case.

| Dataset  | Technique       | DSR   | LeNet1 | LeNet4 | LeNet5 |
|----------|-----------------|-------|--------|--------|--------|
| MNIST    | DeepXplore light| 0.697 | 0.703  | 0.796  |
|          | DeepXplore occl | 0.839 | 0.845  | 0.806  |
|          | DeepXplore blackout | 0.623 | 0.596  | 0.650  |
|          | DLFuzz          | 0.933 | 0.893  | 0.929  |
|          | DAEGEN          | 1.0   | 1.0    | 1.0    |

| Dataset  | Technique       | DSR   | Dave-Orig | Dave-Drop | Dave-Norm |
|----------|-----------------|-------|-----------|-----------|-----------|
| Driving  | DeepXplore light| 0.212 | 0.451     | 0.435     |
|          | DeepXplore occl | 1.00  | 1.00      | 0.782     |
|          | DeepXplore blackout | 0.005 | 0.091     | 0.115     |
|          | DAEGEN          | 1.0   | 1.0       | 1.0       |

**Precision.** Figure 3 shows the distributions of \(L_2\) associated with each technique and dataset. Each bar indicates the number of adversarial examples generated (y axis) for a given range of \(L_2\) values (x axis). Overall, the results of DeepXplore on \(L_2\) are not consistent. For example, for the MNIST dataset, DeepXplore occl and blackout produced examples with lower \(L_2\) values than DAEGEN. On the Driving dataset, however, every configuration of DeepXplore produced examples with high \(L_2\) values. Considering the distribution of DLFuzz on the MNIST dataset, note that most examples have \(L_2\) in the 2.6-2.7 range, which is relatively low.

DAEGEN produced examples in both datasets with similar values for \(L_2\). Compared to the DeepXplore combinations on the Driving dataset, DAEGEN produced examples with considerably smaller \(L_2\) values. However, it produced examples with high \(L_2\) values on the MNIST dataset. Three reasons justify that result. First, the number of queries DAEGEN uses to produce an attack influences on \(L_2\)—a higher number of queries produces more noise on an image. We observed that the Pearson’s correlation between the number of queries and \(L_2\) was, in fact, moderate (\(\sim 0.6\)). Second, DAEGEN generates noise with values ranging in the 0-255 interval. If a noised pixel has a value that is distant from the original pixel value (e.g., the original pixel value is 0 and the noised pixel value is 255), this difference is likely to result in a higher \(L_2\) value. In contrast, DeepXplore and DLFuzz use other criteria to determine the range of perturbation. For example, DeepXplore uses a loss function based on the gradients of the NN to determine the range of perturbation. Third, DAEGEN stops when the search finds the first adversarial example for a given seed input.

It is important to note that it remains an open research problem the identification of a threshold for a given norm (e.g., \(L_2\)) below which a human would unlikely be able to detect differences in a pair of images (Rony et al. [2018]).
other words, high $L_2$ values do not necessarily invalidate an adversarial input. Figure 4 shows inputs that DAEGEN creates, with increasing values of $L_2$ from left to right, to illustrate that.

The first row shows example images from the MNIST dataset with $L_2$ values of 1, 2, 5 and 10, respectively. The impact of perturbations as the norm increases is noticeable in this case. In contrast, the impact of the perturbations is less noticeable on the ImageNet example (Deng et al. [2009]), on the second row, and the Driving example, on the third row. For comparison, the four images of a drake duck have associated $L_2$ values of 5, 10, 50, and 100, respectively. To sum up, human perception is not a function of $L_2$ alone. The resolution of the image also plays a role in that.

**Efficiency.** Figure 5 shows the distributions of time (as histograms) associated with the execution of each technique on each dataset. As expected for a black-box technique, DAEGEN is significantly more efficient than white-box alternatives.

*Summary:* We compared DAEGEN with two other differential techniques (DeepXplore and DLFuzz) on two datasets (MNIST and Driving) and various NN models. DAEGEN was the only technique to generate adversarial examples in all cases analyzed and was the fastest technique.

The norms of the examples created are relatively low.

### 5.3 Black-box (Non-differential) Techniques

This section elaborates on the comparison of DAEGEN with black-box techniques.
5.3.1 Comparison Techniques. We selected two state-of-the-art black-box non-differential techniques for comparison with DAEGEN, namely Simba (Guo et al. [2019]) and Tremba (Huang and Zhang [2020]). Simba searches for adversarial inputs using the $L_2$ norm as DAEGEN does. At each search iteration, Simba samples a vector from a predefined orthonormal basis and either adds that vector or subtracts it to the target image. Tremba is a technique that relies on the transferability property of neural networks (Dong et al. [2019]) to perform adversarial attacks. First, it learns a low-dimensional embedding using a pre-trained model. Then, it performs an efficient search within the embedding space to attack an unknown target network. The method is query efficient and achieves high success rates, thereby producing adversarial perturbations with high-level semantic transferable patterns. The tools implementing these techniques are available from open-source repositories. We used the most recent version of the code and only updated versions of libraries (e.g., PyTorch) to assure that the techniques perform at their best.

5.3.2 Datasets and Models. We used the ImageNet (Deng et al. [2009]) dataset in the evaluation. ImageNet is a large image dataset, containing nearly 15 million images divided into 22K classes. As the original dataset is no longer publicly available, we used the dataset made available by Huang et al. in the evaluation of Tremba \(^1\) (Huang and Zhang [2020]). This reduced dataset contains 22K images, with one image per class. Table 4 shows the datasets and models used in the evaluation.

\(^1\)Available at https://github.com/TransEmbedBA
Table 4. Benchmarks and Models used for comparison with Black-Box techniques.

| Datasets | Model (Source) | Used at          |
|----------|----------------|------------------|
| ImageNet | Densenet121 (Huang et al. [2017]) | Huang and Zhang [2020] |
|          | MobilenetV2 (Sandler et al. [2018]) |                    |
|          | ResNet34 (He et al. [2016]) |                    |
|          | VGG16 (Simonyan and Zisserman [2014]) |                  |
|          | VGG19 (Simonyan and Zisserman [2014]) |                  |

In contrast with the comparison against white-box techniques, this experiment only uses one dataset. The rationale is that we found that the implementation of Tremba and Simba depend on the format of files they accept on input. For example, Simba performs algebraic operations on 3-dimensional matrices, representing the images. These operations are invalid on 2-dimensional matrices, such as those from the MNIST dataset. In principle, changing the implementation of these tools to consider different formats is possible. However, we preferred to discard additional datasets instead of changing the code of the tools, as the later could result in the introduction of bias in the evaluation. We used models commonly used to evaluate the performance of input generation techniques on this dataset.

5.3.3 Setup. Every technique uses a budget of 10K queries to search for an adversarial input, stops when it finds the first adversarial input, and runs on the same set of 100 randomly selected images from the ImageNet dataset. We used the same number of queries used in prior work and chose 100 as the number of seed images to finish the execution.
of experiments in an acceptable time. Considering this setup, our script runs the experiments in approximately 21h – DAEGEN runs for 10h08m, Simba runs for 7h22m, and Tremba runs for 3h22m. We ran the techniques according to the guidelines for replicating their experimental results (sim [2020], tre [2020]) and calculated DSR according to the definition from Section 5.1. Recall that to compare DAEGEN (differential) with Simba and Tremba (non-differential), we created a pipeline of two NNs to simulate differential behavior for the non-differential techniques.

5.3.4 Results. Table 5 summarizes results. The DSR of Simba and Tremba are similar and considerably lower than that of DAEGEN, which was successful in generating adversarial inputs in 99.2% of the cases. Simba produced images with the lowest $L_2$ among the techniques and Tremba produced images with the highest $L_2$, almost twice as high as for the images that DAEGEN produced. Considering the number of queries to the models, DAEGEN required a higher number of queries but that number is well below the 10K budget.

Table 5. Average results comparing DAEGEN and Black-Box techniques: Simba (Guo et al. [2019]) and Tremba (Huang and Zhang [2020])

| Dataset | Technique | DSR | $L_2$ | #Queries |
|---------|-----------|-----|------|---------|
| MNIST   | Simba     | 0.731 | 3.147 | 559.0   |
|         | Tremba    | 0.769 | 11.221| 424.1   |
|         | DAEGEN    | 0.992 | 5.900 | 949.8   |

Effectiveness. Recall that DAEGEN is a differential technique. It produces DIAEs (see Section 1) on output. Existing black-box techniques are non-differential; they do not produce DIAEs on output. DSR enables us to compare effectiveness of these techniques on the same grounds and, consequently, circumvent this problem. Section 5.1 defines DSR for differential and non-differential techniques. In both cases, DSR evaluates effectiveness of a technique on a pair of models. Non-differential DSR checks, for a given pair of models $(a, b)$, whether or not the adversarial input produced by a (non-differential) technique for the model $a$ results in a different output when fed to $b$. Effectively, DSR measures the ability of each technique to produce DIAEs.

Table 6 shows DSR values obtained by each technique for every pair of model combination. The dashes on the DAEGEN section of the table indicate that DAEGEN produces the same results regardless of the order of input models. For example, the result of DAEGEN on the pair $(\text{Densenet121, MobilenetV2})$ is the same as $(\text{MobilenetV2, Densenet121})$. As results show, considering the ability to generate DIAEs, DAEGEN is superior to Tremba and Simba in every one of the 20 combinations of models we analyzed. In 10 combinations DAEGEN had a perfect DSR score. In the rest of the combinations, DAEGEN obtained a score of no less than 97.7%. In contrast, Tremba produced a DSR score above 90% in only one of the combinations: $(\text{VGG16, MobilenetV2})$.

Precision Figure 6 shows the distributions of the $L_2$ norm for each technique. Note that Simba produces examples with the lowest values of $L_2$, but it produces less examples compared to DAEGEN.

Efficiency. Figure 7 shows the distributions of number of queries for each technique. Results indicate that DAEGEN required a higher number of queries compared to alternative techniques.
Table 6. DSR values for black-box techniques for every pair of model combination.

| Networks   | Densenet121 | MobilenetV2 | ResNet34 | VGG16 | VGG19 |
|------------|-------------|-------------|----------|-------|-------|
| Simba      | Densenet121 | NA          | 0.769    | 0.733 | 0.765 | 0.765 |
|            | MobilenetV2 | 0.822       | NA       | 0.842 | 0.839 | 0.835 |
|            | ResNet34    | 0.719       | 0.696    | NA    | 0.711 | 0.700 |
|            | VGG16       | 0.744       | 0.700    | 0.728 | NA    | 0.731 |
|            | VGG19       | 0.649       | 0.628    | 0.638 | 0.613 | NA    |
| Tremba     | Densenet121 | NA          | 0.817    | 0.779 | 0.820 | 0.820 |
|            | MobilenetV2 | 0.792       | NA       | 0.828 | 0.883 | 0.883 |
|            | ResNet34    | 0.766       | 0.815    | NA    | 0.712 | 0.661 |
|            | VGG16       | 0.807       | 0.909    | 0.767 | NA    | 0.486 |
|            | VGG19       | 0.807       | 0.883    | 0.704 | 0.445 | NA    |
| DAEGEN     | Densenet121 | NA          | 1.0      | 1.0   | 1.0   | 1.0   |
|            | MobilenetV2 | —           | NA       | 1.0   | 0.989 | 0.989 |
|            | ResNet34    | —           | —        | NA    | 0.988 | 0.988 |
|            | VGG16       | —           | —        | —     | NA    | 0.977 |
|            | VGG19       | —           | —        | —     | —     | NA    |

Fig. 6. Distributions of $L_2$.

Fig. 7. Distributions of number of queries.

Summary: We compared DAEGEN with two other black-box techniques (Simba and Tremba) on their ability to produce DIAEs. We used a popular dataset (ImageNet) and five NN models in the comparison. DAEGEN was able to produce DIAEs in 99.2% of the cases whereas Simba and Tremba produced DIAEs on rates of 73.1% and 76.9%, respectively. Considering the norm, DAEGEN produced images with much lower $L_2$ values than Tremba and slightly higher values than Simba.
5.4 Threats to Validity

As is the case of most empirical evaluations, there are external, internal, and construct threats to the validity of the experimental results we reported.

External. As usual, the extent of generalization of results are limited to the observations we obtained from our data, including the datasets, models, and techniques we selected in this study. To mitigate this threat, we carefully selected a wide variety of datasets and models available for the corresponding task. We analyzed the MNIST, ImageNet, and Driving datasets, which are popular in this domain. The models we selected are commonly used to evaluate related techniques, use different architectures, and were pretrained on the corresponding datasets. Note that there is an increasing variety of NN architectures available in the literature. We focused on models previously trained and used for evaluating related techniques. Considering the techniques, we selected the state-of-the-art in research. We focused on differential white-box techniques (namely, DeepXplore (Pei et al. [2017]) and DLFuzz (Guo et al. [2018])) as to evaluate the impact of the black-box contribution and on non-differential black-box techniques (namely, Simba [Guo et al., 2019] and Tremba (Huang and Zhang [2020])) as to evaluate the impact of the differential contribution.

Internal. As typical for a human activity (coding), the implementation of DAEGEN or the scripts we used to evaluate DAEGEN could have (unintentional) problems. To mitigate this issue, the authors cross-checked the results reported in this section. Every author analyzed the data individually and pointed to incoherences when they appeared.

Construct. As usual, the plausibility of the metrics we used to evaluate DAEGEN could be questioned. We evaluated DAEGEN on effectiveness, precision, and efficiency as we consider these key quality indicators of an input generation technique. Considering effectiveness, we measured the ability of techniques to produce DIAEs, which is the central goal of our technique. To fairly compare non-differential with differential techniques, we needed to simulate differential behavior, as described on Section 5.1.1. We made our best to fairly evaluate black-box (non-differential) techniques and we believe the evaluation is valuable, but these techniques were not designed for that purpose. Considering precision, there are different norms in the literature to evaluate image similarity. The Euclidean distance ($L_2$) is the most popular norm in related research.

6 RELATED WORK

This section discusses most related work.

6.1 Black-box Input Generation

There are three main categories of adversarial attacks: white-box, gray-box, and black-box (Serban and Poll [2018]) (Xu et al. [2019]). Many white-box techniques have been proposed recently in the literature. These technique typically use a gradient search to generate adversarial examples (e.g., Fast Gradient Sign Method (FGSM) (Goodfellow et al. [2014b]), Projected Gradient Descent (PGD) (Carlini and Wagner [2017]) (Madry et al. [2017]), and $L_{\infty}$ Basic Iterative Attack (Kurakin et al. [2016])). See Yuan et al. [2017] and Zhang and Liang [2019] for a survey of techniques. A white-box attack is better suited when the attacker has access to the implementation of the NN, which is more likely to occur during the development and testing phases. Once the model is deployed, it can be seen as a black-box system (Yuan et al. [2017]), making it hardly practical to apply white-box approaches. It is also worth noting that techniques have been recently proposed to defend against gradient-based attacks. Such defenses can manipulate the gradients performing gradient masking or obfuscation (Alzantot et al. [2019]) (Athalye et al. [2018]). In a gray-box setting, the attacker
has some knowledge about the target network (e.g., architecture, train dataset, or defenses mechanism), but not the gradients. In a black-box setting, the target model is available as a black-box function. Therefore, the attacker is oblivious to critical and essential information about the target model. This is a realistic characterization of the availability of NN models in the real-world. (Serban and Poll [2018]) describe adversarial examples and a threat model for this kind of attack.

Most existing approaches of black-box attacks are considered ineffective since they require hundreds of thousands of queries to the model to generate a single adversarial example (Chen et al. [2017]) (Mosli et al. [2019]). Depending on the model, this could be time-consuming and rely on substantial computational power, therefore, making the attack not practical. Another disadvantage is that some methods often propose the design and implementation of a surrogate model to approximate the decision boundary of the target NN and then apply gradient-descent optimization on the surrogate model, which is also the case in white-box settings (Huang and Zhang [2020]). However, in a black-box setting, the limited number of queries makes these approaches hard to apply as the surrogate model has to, in broad terms, learn the outputs of the target model. Also, training a surrogate model can be challenging due to the complexity and non-linearity in the classification rules, which can degrade the performance of black-box methods (Tu et al. [2019]). Also, it has been found that adversarial training (i.e., using adversarial examples to retrain the model (Ilyas et al. [2019]) combined with gradient-descent techniques (e.g., FGSM and PGD) makes NN models more robust to white-box attacks (Tramèr et al. [2018]). By inference, this combination can be the case of surrogate-based black-box attacks. The implication of this is that models submitted to adversarial training may be robust to surrogate techniques. However, it can still be affected by adversarial examples generated by black-box techniques (Tramèr et al. [2018]), e.g., those that apply local or global search meta-heuristics to generate adversarial examples.

### 6.2 Differential Testing

Pei et al. [2019] proposed DeepXplore, a white-box testing framework for large-scale deep learning systems. DeepXplore formulates search as a joint optimization problem of generating inputs that maximize neuron coverage and maximize the differential behaviors (or merely the differences) of multiple similar DL systems. Besides the white vs. black box differences, DeepXplore and DAEGEN formulate different optimization problems. DeepXplore maximizes differential behavior across various neural nets, while DAEGEN considers only two neural networks during the attack.

The solution proposed by Papernot et al. [2017] also involves multiple models. Their solution builds on the concept of transfer-based attacks, i.e., the adversarial examples crafted for the surrogate models can be then used to attack other models. The adversarial examples prepared by DAEGEN were not tested against other models besides the models involved in the attack. We can only say that, in some cases, it can attack both models in the attack configuration, but in the other cases, it can only attack one of the models.

### 6.3 Optimization-based Adversarial Example Generation

In recent studies, we note the use of optimization techniques to generate adversary examples. In these studies, there exists some concern in minimizing the amount of queries needed to rediscover the attack until an adverse example is produced. (Chen et al. [2019]) and (Alzantot et al. [2019]) have proposed genetic algorithms. In the first work, a new optimized black-box attack was proposed, based on the genetic algorithm (POBA-GA), capable of generating approximate optimal opponents through evolutionary operations, including initialization, selection, crossover, and mutation. In the second work, a new gradient-free optimization technique (GenAttack) that uses genetic algorithms to generate adversary examples was proposed. GenAttack can successfully attack some advanced defense techniques for
ImageNet, suggesting that evolutionary algorithms are promising in promoting black-box attacks. Both works perform targeted attacks (while DAEGEN only performs non-targeted attacks) and formulate their optimization problem as a multi-objective optimization problem, where they try to maximize the probability $P(y|X)$ for a specified $y$. (Chen et al. [2019]) also try to minimize the difference between the original image and the adversarial image, and (Alzantot et al. [2019]) try to minimize the probability of $P(\neg y|X)$. Therefore, the difference between these threat models and DAEGEN relies on the fact that it solves the optimization problem by trying to maximize the difference between the probability $P(y|X)_a$ and the probability $P(y|X)_b$, for a pair of models $M_a$ and $M_b$ respectively.

Other more sophisticated techniques such as Zeroth Order Optimization have been applied in (Chen et al. [2017]) and (Cheng et al. [2019]). Particle swarm optimization (PSO) is present in the works (Mosli et al. [2019]) and (Zhang et al. [2019]). PSO can quickly converge on sufficiently good solutions with few queries. Like the Genetic Algorithm, PSO also requires the design of fitness function. Both (Mosli et al. [2019]) and (Zhang et al. [2019]) opt for fitness functions that are equations containing the output of the network for a given particle (possible adversarial solution) and the L2 norm of the original image and the particle.

Although many meta-heuristics optimization approaches have natural methods to randomly introduce small noises and perturbations into inoffensive image samples in their search for feasible (or optimal) solutions, we must mention that they are not the only options. Generative Adversarial Networks (GANs) (Goodfellow et al. [2014a]) are also viable options to generate candidate solutions for the optimization algorithms (Xiao et al. [2018]) (Fang et al. [2019]). Bayesian optimization (Shukla et al. [2019]) and random fuzzing (Zhang et al. [2019]) are also interesting approaches for black-box attacks. However, these techniques are usually a more sophisticated solution for the adversarial generation problem. For the sake of simplicity, we chose to apply custom implementations of search-based optimization techniques, namely, Hill Climbing, with minimal modifications to satisfy our attack-method requirements.

7 CONCLUSIONS

We presented DAEGEN, a black-box method to exploit differential behavior between two neural networks by finding difference-inducing adversarial examples (DIAEs) that maximize their output difference (under constraints on the perturbation). We conducted a comprehensive set of experiments to evaluate DAEGEN. We considered existing white-box methods that can generate DIAEs and then adapted existing black-box methods to work on DIAEs. Our experiments show the superiority of DAEGEN over all of them in terms of effectiveness, precision, and efficiency.

We compared DAEGEN with two other differential techniques (DeepXplore and DLFuzz) on two datasets (MNIST and Driving) and various NN models. DAEGEN was the only technique to generate adversarial examples in all cases analyzed and was the fastest technique. Besides, we compared DAEGEN with two other non-differential black-box techniques (Simba and Tremba) on their ability to produce DIAEs. We used a popular dataset (ImageNet) and five NN models in the comparison. We found that DAEGEN was able to produce DIAEs in 99.2% of the cases, whereas Simba and Tremba produced DIAEs on rates of 73.1% and 76.9%, respectively.

Our findings can help in the development of techniques to test, evaluate, and ensure robustness of neural networks against black-box adversarial attacks, especially in security-critical domains. Future work will focus on improving DSR to achieve a 100% success rate and validating our approach against known defense methods. It will also be a natural next step to see whether DAEGEN can be used to support explainable AI. We believe that a good explanation of neural network behavior may be achievable through identifying the differences between neural networks.
REFERENCES

2020. DLFuzz repository. https://github.com/tumerd270/DFuzz.
2020. DeepXplore repository. https://github.com/perkevin9/deepxplore.
2020. Simba repository. https://github.com/cj6363/simple-blackbox-attack.
2020. Tremba repository. https://github.com/TransEmbedBA.

Abdullahi Adamu, Tomás Masl, Andrzej Bargiela, and Christopher Road knight. 2015. Preliminary Experiments with Ensembles of Neuroally Diverse Artificial Neural Networks for Pattern Recognition. In Proceeding of the 38th International Conference on Machine Learning. (Proceedings of Machine Learning Research, Vol. 80). Jennifer Dy and Andreas Krause (Eds.). PMLR, Stockholm, Sweden, 274–283.

Moustafa Alzantot, Yash Sharma, Supriyo Chakraborty, Huan Zhang, Cho-Jui Hsieh, and Mani B. Srivastava. 2019. GenAttack: Practical Black-Box Attacks with Gradient-Free Optimization. In Proceedings of the Genetic and Evolutionary Computation Conference, GECCO 2019, Prague, Czech Republic, July 15-19, 2019, Anne Auger and Thomas Stützle (Eds.). Association for Computing Machinery, New York, NY, USA, 1111–1119. https://doi.org/10.1145/3321707.3321749

Anish Athalye, Nicholas Carlini, and David Wagner. 2018. Obfuscated Gradients Give a False Sense of Security: Circumventing Defenses to Adversarial Examples. In Proceedings of the 35th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 80). Jennifer Dy and Andreas Krause (Eds.). PMLR, Stockholm, Sweden, 274–283.

Chuan Guo, Jacob R. Gardner, Yurong You, Andrew Gordon Wilson, and Kilian Q. Weinberger. 2019. Simple Black-box Adversarial Attacks. ArXiv abs/1912.01667 (2019). 32.

Mariusz Bojarski, Davide Del Testa, Daniel Dworakowski, Bernhard Firner, Beat Flepp, Prasoon Goyal, Lawrence D. Jackel, Mathew Monfort, Urs Muller, Jiakai Zhang, Xin Zhang, Jake Zhao, and Karol Zieba. 2016. End to End Learning for Self-Driving Cars. CoRR abs/1604.07316 (2016). arXiv:1604.07316

N. Carlini and D. Wagner. 2017. Towards Evaluating the Robustness of Neural Networks. In 2017 IEEE Symposium on Security and Privacy (SP). IEEE, San Jose, CA, USA, 39–57. https://doi.org/10.1109/SP.2017.49

Anirban Chakraborty, Manaar Alam, Vishal Dey, Anupam Chattopadhyay, and Debdeep Mukhopadhyay. 2018. Adversarial Attacks and Defences: A Survey. CoRR abs/1810.00669 (2018). arXiv:1810.00669

Jinyin Chen, Mengmeng Su, Shujing Shen, Hui Xiong, and Haibin Zheng. 2019. POBA-GA: Perturbation optimized black-box adversarial attacks via genetic algorithm. Computers & Security 85 (2019), 89 – 106. https://doi.org/10.1016/j.cose.2019.04.014

Pin-Yu Chen, Huan Zhang, Yash Sharma, Junfeng Yi, and Cho-Jui Hsieh. 2017. ZOO: Zeroth Order Optimization Based Black-box Attacks to Deep Neural Networks Without Training Substitute Models. In Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security (AI Sec ’17). Association for Computing Machinery, New York, NY, USA, 15–26.

Manhao Cheng, Thong Lin, Pin-Yu Chen, Huan Zhang, Junfeng Yi, and Cho-Jui Hsieh. 2019. Query-Efficient Hard-label Black-box Attack: An Optimization-based Approach. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. OpenReview.net, 14. https://openreview.net/forum?id=cflK6gRXK

J. Deng, W. Dong, R. Socher, L. Li, Kai Li, and Li Fei-Fei. 2009. ImageNet: A large-scale hierarchical image database. In 2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2009), 20-25 June 2009, Miami, Florida, USA. IEEE, Washington, DC, USA, 248–255. https://doi.org/10.1109/CVPR.2009.5206848

Yinpeng Dong, Tianyu Pang, Hang Su, and Jun Zhu. 2019. Evading Defenses to Transferable Adversarial Examples by Translation-Invariant Attacks. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (Jun 2019). https://doi.org/10.1109/cvpr.2019.00444

Xiaoyu Fang, Guoxu Cao, Huapeng Song, and Zhiyou Ouyang. 2019. XGAN: adversarial attacks with GAN. In 2019 International Conference on Image and Video Processing, and Artificial Intelligence, Ruidan Su (Ed.), Vol. 11321. International Society for Optics and Photonics, SPIE, 322 – 327. 10.1117/12.2534218

Patrice Godefroid. 2020. Fuzzing: hack, art, and science. Commun. ACM 63, 2 (2020), 70–76. https://doi.org/10.1145/3363824

Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014a. Generative Adversarial Nets. In Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada (NIPS’14). Zoubin Ghahramani, Max Welling, Corinna Cortes, Neil D. Lawrence, and Kilian Q. Weinberger (Eds.). MIT Press, Cambridge, MA, USA, 2672–2680.

Ian J. Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014b. Explaining and Harnessing Adversarial Examples. CoRR abs/1412.6572 (2014). 11.

Chuan Guo, Jacob R. Gardner, Yurong You, Andrew Gordon Wilson, and Kilian Q. Weinberger. 2019. Simple Black-box Adversarial Attacks. CoRR abs/1905.07121 (2019). arXiv:1905.07121

Jianmin Guo, Yu Jiang, Yue Zhao, Quan Chen, and Jiaguang Sun. 2018. DLFuzz: Differential Fuzzing Testing of Deep Learning Systems. In Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, 739–743.

T. Guo, J. Dong, H. Li, and Y. Gao. 2017. Simple convolutional neural network on image classification. In 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA) IEEE, 721–724. https://doi.org/10.1109/ICBDA.2017.8078730

K. He, X. Zhang, S. Ren, and J. Sun. 2016. Deep Residual Learning for Image Recognition. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, Las Vegas, NV, USA, 770–778. https://doi.org/10.1109/CVPR.2016.90
Generating Adversarial Inputs Using A black-box Differential Technique

Gao Huang, Zhang Liu, L. v. d. Maaten, and Kilian Q. Weinberger. 2017. Densely Connected Convolutional Networks. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017. IEEE, 2261–2269. https://doi.org/10.1109/CVPR.2017.243

Xiaowei Huang, Daniel Kroening, Wanjie Ruan, James Sharp, Youcheng Sun, Emese Thamo, Min Wu, and Xinquing Yi. 2018. A Survey of Safety and Trustworthiness of Deep Neural Networks. arXiv preprint arXiv:1812.08342 (2018).

Zhichao Huang and Tong Zhang. 2020. Black-Box Adversarial Attack with Transferable Model-based Embedding. In International Conference on Learning Representations. ICLR. https://openreview.net/forum?id=SJchNTNYwB

Andrew Ilyas, Logan Engstrom, Anish Athalye, and Jessy Lin. 2018. Black-box Adversarial Attacks with Limited Queries and Information. ArXiv abs/1804.08598 (2018), 10.

Andrew Ilyas, Shibani Santurkar, Dimitris Tsipras, Logan Engstrom, Brandon Tran, and Aleksander Madry. 2019. Adversarial Examples Are Not Bugs, They Are Features. arXiv e-prints, Article arXiv:1905.02175 (May 2019), arXiv:1905.02175 pages. arXiv:1905.02175 [stat.ML]

Andrew Ilyas, Shibani Santurkar, Dimitris Tsipras, Logan Engstrom, Brandon Tran, and Aleksander Madry. 2019. Adversarial Examples Are Not Bugs, They Are Features. In Advances in Neural Information Processing Systems 32; H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alché-Buc, E. Fox, and R. Garnett (Eds.). Curran Associates, Inc., Vancouver, BC, Canada, 125–136. http://papers.nips.cc/paper/8307-adversarial-examples-are-not-bugs-they-are-features.pdf

U. Johansson, T. Lofstrom, and N. Niskanen. 2007. The Importance of Diversity in Neural Network Ensembles - An Empirical Investigation. In 2007 International Joint Conference on Neural Networks. 661–666.

C. Juang, C. Chiu, and C. Lai. 2007. Hierarchical Singleton-Type Recurrent Neural Fuzzy Networks for Noisy Speech Recognition. IEEE Transactions on Neural Networks 18, 3 (May 2007), 833–843. https://doi.org/10.1109/TNN.2007.891194

Alexey Kurakin, Ian J. Goodfellow, and Samy Bengio. 2016. Adversarial examples in the physical world. ArXiv abs/1607.02533 (2016), 14.

Yann Lecun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. 1998. Gradient-based learning applied to document recognition. Proc. IEEE 86, 11 (Nov 1998), 2278–2324. https://doi.org/10.1109/5.726791

Yanpedi Liu, Xinyun Chen, Chang Liu, and Dawn Song. 2017. Delving into Transferable Adversarial Examples and Black-box Attacks. In ICLR2017.

Jiajun Lu, Hussein Sibai, Evan Fabry, and David A. Forsyth. 2017. NO Need to Worry about Adversarial Examples in Object Detection in Autonomous Vehicles. CoRR abs/1707.03501 (2017). arXiv:1707.03501 http://arxiv.org/abs/1707.03501

Alex Lubben. 2018. Self-driving Uber killed a pedestrian as human safety driver watched. www.vice.com/en_us/article/kxzqby/self-driving-uber-killed-a-pedestrian-as-human-safety-driver-watched [Online; Accessed on April 3, 2020].

Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. 2017. Towards Deep Learning Models Resistant to Adversarial Attacks. ArXiv abs/1706.06083 (2017), 28.

William M. McKeeman. 1998. Differential Testing for Software. DIGITAL TECHNICAL JOURNAL 10, 1 (1998), 100–107.

Rayan Mosdi, Matthew Wright, Bo Yuan, and Yin Pan. 2019. They Might NOT Be Giants: Crafting Black-Box Adversarial Examples with Fewer Queries Using Particle Swarm Optimization. ArXiv abs/1909.07490 (2019), 13.

Nicolas Papernot, Patrick McDaniel, Ian Goodfellow, Somesh Jha, Z. Berkay Celik, and Ananthram Swami. 2017. Practical Black-Box Attacks against Machine Learning. In Proceedings of the 2017 ACM on Asia Conference on Computer and Communications Security Association for Computing Machinery, New York, NY, USA, 506–519. https://doi.org/10.1145/3052973.3053009

Nicolas Papernot, Patrick D. McDaniel, Ian J. Goodfellow, Somesh Jha, Z. Berkay Celik, and Ananthram Swami. 2016. Practical Black-Box Attacks against Deep Learning Systems using Adversarial Examples. CoRR abs/1602.02697 (2016). arXiv:1602.02697 http://arxiv.org/abs/1602.02697

Kexin Pei, Yinzhi Cao, Junfeng Tang, and Suman Jana. 2017. DeepXplore: Automated Whitebox Testing of Deep Learning Systems. In Proceedings of the 26th Symposium on Operating Systems Principles (SOSP’17). 1–18.

Kexin Pei, Yinzhi Cao, Junfeng Tang, and Suman Jana. 2019. DeepXplore: Automated Whitebox Testing of Deep Learning Systems. Commun. ACM 62, 11 (Oct. 2019), 137–145. https://doi.org/10.1145/3361566

Jérôme Rony, Luiz G. Hafemann, Luiz S. Oliveira, Ismail Ben Ayed, Robert Sabourin, and Eric Granger. 2018. Decoupling Direction and Norm for Efficient Gradient-Based L2 Adversarial Attacks and Defenses. CoRR abs/1811.09600 (2018). arXiv:1811.09600 http://arxiv.org/abs/1811.09600

Stuart Russell and Peter Norvig. 2009. Artificial Intelligence: A Modern Approach (3rd ed.). Prentice Hall Press, USA.

Mark Sandler, Andrew G. Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. 2018. MobileNetV2: Inverted Residuals and Linear Bottlenecks. In 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018. IEEE, 4510–4520. https://ieeexplore.ieee.org/xpl/conhome/8576498/proceeding

Nandini Sengupta, Md Sahidullah, and Goutam Saha. 2016. Lung sound classification using cepstral-based statistical features. Computers in Biology and Medicine 75 (2016), 118 – 129. https://doi.org/10.1016/j.compbiomed.2016.05.013

Alexandru Constantin Serban and Erik Poll. 2018. Adversarial Examples – A Complete Characterisation of the Phenomenon. ArXiv abs/1810.01185 (2018), 56.

Satya Narayan Shukla, Akil Kumar Saha, Devin Willmott, and J. Zico Kolter. 2019. Black-box Adversarial Attacks with Bayesian Optimization. ArXiv abs/1909.13857 (2019), 12.

Karen Simonyan and Andrew Zisserman. 2014. Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv:1409.1556 [cs.CV]

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian J. Goodfellow, and Rob Fergus. 2013. Intriguing properties of neural networks. CoRR abs/1312.6199 (2013), 10.
Florian Tramèr, Alexey Kurakin, Nicolas Papernot, Ian Goodfellow, Dan Boneh, and Patrick McDaniel. 2018. Ensemble Adversarial Training: Attacks and Defenses. *In International Conference on Learning Representations* ICRL, Toulon, France. https://openreview.net/forum?id=rkZvSe-RZ.

Chun-Chen Tu, Paishun Ting, Pin-Yu Chen, Sijia Liu, Huan Zhang, Jinfeng Yi, Cho-Jui Hsieh, and Shin-Ming Cheng. 2019. AutoZOOM: Autoencoder-Based Zeroth Order Optimization Method for Attacking Black-Box Neural Networks. *Proceedings of the AAAI Conference on Artificial Intelligence* 33 (07 2019), 742–749. https://doi.org/10.1609/aaai.v33i01.3301742

udacity challenge. 2016. Udacity Self-Driving Car (Dataset). https://github.com/udacity/self-driving-car.

Bill Vlasic and Neal E. Boudette. 2016. Self-Driving Tesla Was Involved in Fatal Crash, U.S. Says. www.nytimes.com/2016/07/01/business/self-driving-tesla-fatal-crash-investigation.html. [Online; Accessed on April 3, 2020].

Waymo. 2020. Waymo open dataset. https://waymo.com/open/.

Chaoqun Xiao, Bo Li, Jun Yang Zhu, Warren He, Mingyan Liu, and Dawn Song. 2018. Generating Adversarial Examples with Adversarial Networks. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI 2018*, July 13-19, 2018, Stockholm, Sweden, Jérôme Lang (Ed.). ijcai.org, null, 3905–3911. https://doi.org/10.24963/ijcai.2018/543

Han Xu, Yao Ma, Haschen Liu, Debayan Deb, Hui Liu, Jiliang Tang, and Anil K. Jain. 2019. Adversarial Attacks and Defenses in Images, Graphs and Text: A Review. arXiv:1909.08072 [cs.LG]

M. Yeo, Y. Koo, Y. Yoon, T. Hwang, J. Ryu, J. Song, and C. Park. 2018. Flow-based malware detection using convolutional neural network. In *2018 International Conference on Information Networking (ICOIN)*. IEEE, Chiang Mai, Thailand, 910–913. https://doi.org/10.1109/ICOIN.2018.8343255

Xiaoyong Yuan, Pan He, Qile Zhu, and Xiaolin Li. 2017. Adversarial Examples: Attacks and Defenses for Deep Learning. *IEEE Transactions on Neural Networks and Learning Systems* 30 (2017), 2805–2824.

Q. Zhang, K. Wang, W. Zhang, and J. Hu. 2019. Attacking Black-Box Image Classifiers With Particle Swarm Optimization. *IEEE Access* 7 (2019), 158051–158063. https://doi.org/10.1109/ACCESS.2019.2948146

Y. Zhang and P. Liang. 2019. Defending against Whitebox Adversarial Attacks via Randomized Discretization. In *The 22nd International Conference on Artificial Intelligence and Statistics, AISTATS 2019*, 16-18 April 2019, Naha, Okinawa, Japan (*Proceedings of Machine Learning Research*, Vol. 89), Kamalika Chaudhuri and Masashi Sugiyama (Eds.). PMLR, Naha, Okinawa, Japan, 10. http://proceedings.mlr.press/v89/

Dimitrios Zissis, Elias K. Xidias, and Dimitrios Lekkas. 2015. A Cloud Based Architecture Capable of Perceiving and Predicting Multiple Vessel Behaviour. *Appl. Soft Comput. 55, C* (Oct. 2015), 652–661. https://doi.org/10.1016/j.asoc.2015.07.002