CAGFuzz: Coverage-Guided Adversarial Generative Fuzzing Testing of Deep Learning Systems

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Abstract—With the emerging of big data technology, Deep Learning systems (DL) based on Deep Neural Networks (DNNs) are more and more used in various aspects of our life, including unmanned vehicles, speech processing, and robotics. However, due to the limited dataset and the dependence on manual labeling data, DNNs often fail to detect their erroneous behaviors, which may lead to serious problems. Several approaches have been proposed to enhance the input examples for testing DL systems. However, they have the following limitations. First, most of them do not consider the influence of small perturbations on input examples. Some approaches take into account the perturbations, however, they design and generate adversarial examples from the perspective of model. These examples generated from a specific model may cause low generalization ability when they are applied to other models. Second, they only use surface feature constraints (e.g. pixel-level constraints) to judge the difference between the adversarial example generated and the original example. The deep feature constraints, which contain high-level semantic information, such as image object category and scene semantics are completely neglected. To address these two problems, in this paper, we propose CAGFuzz, a Coverage-guided Adversarial Generative Fuzzing testing approach, which generates adversarial examples for a targeted DNN to discover its potential defects. First, we train an adversarial case generator (AEG) from the perspective of general data set. AEG only considers the data characteristics, and avoids low generalization ability when it is testing other models. Second, we extract the depth features of the original and adversarial examples, and constrain the adversarial examples by cosine similarity to ensure that the semantic information of adversarial examples remains unchanged. Finally, we retrain effective adversarial examples to improve neuron testing coverage rate. Based on several popular data sets, we design a set of dedicated experiments to evaluate CAGFuzz. The experimental results show that CAGFuzz can improve the generalization ability, the neuron coverage rate, detect hidden errors, and also improve the accuracy of the target DNN.

Index Terms—deep neural network; fuzz testing; adversarial example; coverage criteria.

1 INTRODUCTION

Currently, we have already stepped into the era of artificial intelligence from the digital era. Apps with AI systems can be seen everywhere in our daily life, such as Amazon Alexa [1], DeepMind’s Atari [2], and AI-phaGo [3]. Nowadays with the development of edge computing, 5G technology and etc., AI technologies become more and more mature. In many applications, we can see the shape of deep neural networks (DNNs), such as automatic driving [4], intelligent robotics [5], smart city applications [6] and AI-enabled Enterprise Information Systems [7]. In this paper, we term this kind of applications as DL (deep learning) systems.

In particular, many different kinds of DNNs are embedded in security and safety-critical applications, such as automatic driving [4] and intelligent robotics [5]. This brings new challenges since predictability and correctness are crucial for this kind of DL systems. These safety-critical applications deploying DNNs without comprehensive testing could have serious problems. For example, in automatic driving systems, if the deployed DNNs have not recognized the obstacles ahead timely and correctly, it may lead to serious consequences such as vehicle damage and even human death [8].

Generally speaking, the development process of DL systems is essentially different from the traditional software development process. As shown in Fig. [1] for traditional software development practices, developers directly specify the logic of the system. On the contrary, DL systems automatically learn their models and corresponding parameters from data. The testing process of DL systems is also different from traditional software systems. For traditional software systems, code or control-flow coverage is utilized to guide the testing process [9]. However, the logic of the DL systems is not encoded by control flow, and it cannot be solved by the normal encoding way. Its decisions are always made by training data for many times, and the performance is more dependent on data rather than human intervention. For DL systems, neural coverage can be used to guide the testing process [10]. When fault is found, it is also very difficult to locate the exact position in the original DL systems. Consequently, most traditional software testing methodologies are not suitable for testing DL systems. As highlighted in [10], research on developing new testing techniques for DL systems is urgently needed.

The standard way to test DL systems is to collect and
manually mark as much actual test data as possible [11], [12]. Obviously it is unthinkable to exhaustively test every feasible input of the DL systems. Recently, an increasing number of researchers have contributed to testing DL systems with a variety of approaches [10], [13], [14], [15], [16]. The main idea of these approaches is to enhance input examples of test data set by different techniques. Some approaches, e.g. DeepXplore [10], use multiple DNNs to discover and generate adversarial examples that lie between the decision boundaries of these DNNs. Some approaches, e.g. DeepHunter [13], use metamorphic mutation strategy to generate new test examples. Other approaches, e.g. DeepGauge [15], propose new coverage criteria for deep neural networks. These coverage criteria can be used as guidance for generating test examples. While state-of-the-art approaches make some progresses on testing DL systems, they still suffer the following two main problems:

1) Most approaches do not consider the influence of small perturbations on deep neural networks when the test examples are generated. Some approaches considering small perturbations from the perspective of DNN model. The test examples they generated are only used for one special DNN, and may lead to low generalization ability problem for other DNNs. Recent research on adversarial DL systems [17], [18] shows that by adding the small perturbations to existing images, elaborating synthetic images can fool state-of-the-art DL systems. Therefore, to improve the generalization ability, it is significantly important to add small perturbations only from the perspective of data.

2) State-of-the-art adversarial example generation approaches use surface feature constraints, such as pixel-level constraints, to judge the difference between the adversarial example and the original example. The deep feature constraints containing high-level semantic information, such as image object category and scene semantics, are completely neglected. For example, in their study, Xie et al. [13] use $L_0$ and $L_\infty$ to limit the pixel-level changes of the adversarial example. However, such constraints can only represent the visual consistency between the adversarial example and the original example, and cannot guarantee the consistency between the high-level semantics information of the adversarial example and the original example.

To address the problems aforementioned, we propose CAGFuzz [1] a Coverage-guided Adversarial Generative Fuzzing testing approach for DL systems. The goal of the CAGFuzz is to maximize the neuron coverage and generate adversarial test examples as much as possible with minor perturbations for the target DNNs. Meanwhile, the generated examples are suitable for different kinds DNNs. CAGFuzz iterative selects the test examples in the processing pool and generates the adversarial examples through the pre-trained adversarial example generator (see Section 5 for details) to guide the DL systems to expose incorrect behaviors. During the process of generating adversarial examples, CAGFuzz maintains adversarial examples to provide a certain improvement in neuron coverage for subsequent fuzzy processing, and limits the minor perturbations invisible to human eyes, ensuring the same meaningfulness between the original example and the adversarial example. In summary, the contributions of this paper include the following three aspects:

- We design an adversarial example generator, AEG, which can generate adversarial examples with minor perturbations for test examples independent of DNN models. The goal of CycleGAN [19] is to transform image $A$ to image $B$ with different styles. Based on CycleGAN, our goal is to transform image $B$ back to image $A$, so as to get image $A'$ similar to the original image $A$. Consequently, we combine two generators with opposite functions of CycleGAN as our adversarial example generator. The adversarial examples generated by AEG can add minor perturbations invisible to human eyes to the original examples. The adversarial examples are similar to the original examples. At the same time, AEG is trained based on several certain data set and does not need to rely on any specific DNN model, which is more universal and has higher generalization ability than state-of-the-art approaches. Furthermore, because of the inherent constraint logic of CycleGAN, the trained AEG not only has high efficiency in generating adversarial examples but also can effectively improve the robustness of DL systems.

- We extract the depth features of the original example and the adversarial example, and make them as similar as possible by similarity measurement. We use VGG – 19 network to extract the deep semantics information of the original example and the adversarial example, and use the method of cosine similarity measurement to ensure that the depth semantics information of the adversarial example is consistent with the original example as much as possible.

- We particularly design a series of experiments for evaluating the proposed CAGFuzz approach based on several public data sets. The experiments validate that CAGFuzz can effectively improve the neuron coverage of the target DNN model. Meanwhile, it is proved that the adversarial examples generated by CAGFuzz can find hidden defects in the target DNN model. Furthermore, the accuracy and the robustness of the DNN models retrained by AEG have been significantly improved. For example, the accuracy of the VGG – 16 model has been improved from the original 86.72% to 97.25%, with an improvement of 12.14%.

The rest of the paper is organized as follows. Section 2 provides some basic concepts including CycleGAN, coverage-guided fuzz (CGF), and VGG-19 Network Structure. The coverage-guided adversarial generative fuzzy testing framework is provided in Section 3. In Section 4, we use two popular datasets (MNIST [21] and Cifar-10 [22]) to validate our approach. Existing work and their limitations are discussed in Section 5. Finally, Section 6 concludes the paper and looks into future work.

1. https://github.com/QXL4515/CAGFuzz
2 PRELIMINARIES

The principles of coverage-guided grey-box fuzzing, CycleGAN and VGG-19 are introduced in Section 2.1, Section 2.2 and Section 2.3, respectively. Section 2.4 introduces the basic concept and calculation formula for neuron coverage.

2.1 Coverage-guided Grey-box Fuzzing

Due to the scalability and effectiveness in generating useful defect detection tests, fuzzing has been widely used in academia and industry. Based on the perception of the target program structure, the fuzzy controller can be divided into black-box, white-box and grey-box. One of the most successful techniques is coverage-guided grey-box fuzzing (CGF), which balances effectiveness and efficiency by using code coverage as feedback. Many state-of-the-art CGF approaches, such as AFL [23], LibFuzzer [24] and VUzzer [25], have been widely used and proved to be effective. Smart grey-box fuzzing (SGF) [26] has made some improvements on CGF, which leverages a high-level structural representation of the original example to generate new examples. The state-of-the-art CGF approaches mainly consist of three parts: mutation, feedback guidance, and fuzzing strategy:

- **Mutation**: According to the difference of the target application program and data format, the corresponding test data generation method is chosen and it can use the pre-generated examples, a variation of valid data examples, or dynamically generated ones according to the protocol or file format.
- **Feedback guidance**: The fuzzy test example is executed, and the target program is executed and monitored. The test data that causes the exception of the target program is recorded.
- **Fuzzing strategy**: If an error is detected, the corresponding example is reported and new generated examples that cover new traces are stored in the example pool.

2.2 CycleGAN

Adversarial Example Generator (AEG) is an important part of our approach. To improve the stability and security for target DL systems, AEG provides effective adversarial examples to detect potential defects. The idea of generating adversarial examples is to add perturbations that people cannot distinguish from the original examples; this is very similar to the idea of GAN [27] generation of examples. GAN’s generators $G$ and discriminators $D$ alternately generate adversarial examples that are very similar but not identical to the original examples based on noise data. Considering the difference of datasets of different target DL systems, such as some DL systems with label data and other DL systems may not, we choose CycleGAN [19] as the training model of adversarial example generator, since CycleGAN does not require the matching of data sets and label information. CycleGAN is one of the most effective adversarial generation approaches. The mapping function and loss function of CycleGAN are described as follows.

- The goal of CycleGAN is to learn the mapping functions between two domains $X$ and $Y$. There are two mappings $G$ and $F$ in the model. There are two adversarial discriminators $D_x$ and $D_y$, where $D_x$ aims to distinguish between images $\{x\}$ and translated images $\{F(x)\}$. $D_y$ has a similar definition.
- Like other GANs, the adversarial loss function is used to optimize the mapping function. But during the actual training stage, it is found that the negative log-likelihood objective is not very stable and the loss function is changed to least-squares loss [28].
- Because of the group mapping, it is impossible to train by using the adversarial loss function only. The reason is that mapping $F$ can map all $x$ to a picture in $Y$ space, consequently, CycleGAN puts forward the cycle consistency loss.

Fig. 2 shows an example structure of CycleGAN. The purpose of this example is to transform real pictures and Van Gogh style paintings into each other. It does not need pairs of data to guide the adversarial generation, and has a wide range and practicability. Therefore, in this paper, we use CycleGAN to train our adversarial example generator, which can effectively generate adversarial examples to test the target DL systems.

2.3 VGG-19 Network Structure

As a feed-forward neural network, the last layer of CNN has $m$ neurons. Each neuron outputs a scalar. The output of $M$ neurons can be regarded as a vector $v$. Now all of them are connected to one neuron. The output of this neuron is $wv+b$, which is a continuous value and can deal with regression prediction problems. The function of CNN is similar to that of BP neural network. Without explicit mathematical expression, the mapping relationship between input and output is described according to sample data.

The ability of deep feature recognition and semantic expression extracted by CNN is stronger. Consequently, it has more advantages than traditional image features. The structure of VGG-19 [20] convolution network is shown in Fig. 3. There are 19 layers, including 16 convolution layers, i.e. two every Conv11-Conv12, four every Conv13-Conv15, and three full-connection layers, Fc6, Fc7 and Fc8. The results show that VGG-19 network can extract high-level semantic information from images [29], [30], which...
can be used to identify similarities between images. In this paper, the output of the last full connection layer is fused as eigenvector to compare the similarity between the adversarial examples and the original examples, and to serve as the threshold for filtering the generated adversarial examples.

Fig. 3. Structural Chart of VGG19 Network for Extracting Depth Features of Target Images

2.4 Neuron Coverage
Pei et al. [10] propose neuron coverage as a measure of testing DL for the first time. They define neuron coverage of a set of test inputs as the ratio of the number of unique activated neurons in all test inputs to the total number of neurons in the DNN.

Let \( N = \{ n_1, n_2, \ldots \} \) be a number of sets composing all neurons in a DNN and let \( T = \{ x_1, x_2, \ldots \} \) be test inputs. Let \( \text{out}(n, x) \) be an output function that returns the output value of a neuron \( n \) in DNN for a given test input \( x \). Finally, let \( t \) represent the threshold for considering a neuron to be activated. Then, the neuron coverage can be defined in the following:

\[
NC(T, x) = \frac{|\{n | \forall x \in T, \text{out}(n, x) > t\}|}{|N|}
\]  

3 COVERAGE-GUIDED ADVERSARIAL GENERATIVE FUZZING TESTING APPROACH
In this section, we first give an overview of our approach (Section 3.1), then the pre-treatment of our approach is described in Section 3.2 including data collection and AEG training. Section 3.3 describes the algorithm of the adversarial example generation process. Finally, Section 3.4 shows how our approach uses neuron coverage feedback to guide the generation of new adversarial examples.

3.1 Overview
The core component of DL systems is the deep neural network (DNN) with different structures and parameters. In the following discussions, we will study how to test DNN. The input formats of DNN can be various. In this paper, we focus on the input format as pictures. Adding perturbations to images has a great impact on DNN and may cause errors. Guided by neuron coverage, the quality of the generated countermeasure samples can be improved. As anticipated before, this paper presents CAGFuzz, a coverage-guided adversarial generative fuzzing testing approach. The details of the algorithm are shown in Algorithm 1. This approach generates adversarial examples with invisible perturbations based on AEG. In general, Fig. 4 shows the main process of our approach, which consists of three parts, described as follows:

- The first step is the data collection and training adversarial example generator. Given the DNN to be tested and its corresponding data set. The collected data sets are operated in two steps. On the one hand, the data sets are divided into two subsets and as the input of CycleGAN to train AEG. On the other hand, these examples are put into the processing pool after priority is set according to storage time and so on, which serves as the original example set for the fuzzy test.

- The second step is the adversarial example generation. Each time a prioritized raw example is selected from the processing pool and used as the input of AEG to generate adversarial examples. The adversarial examples and the original examples are processed by VGG-19 to extract the feature matrix of the examples. The cosine similarity of the feature matrix between the adversarial examples and the original examples is calculated to ensure that the deep semantics of the adversarial examples are consistent with the original examples.

- The third step is to use neuron coverage to guide the generation process. The adversarial examples generated in the second step is input to the DNN under
test for coverage analysis. If a new coverage occurs, the adversarial example will be put into the processing pool as part of the dataset. The new coverage means that the neuron coverage of the adversarial example is higher than that of the original example.

**Algorithm 1** A description of the main loop of \textit{CAGFuzz}

**Input:** \(D\): Corresponding data sets, 
\(DNN\): Target Deep Neural Network, 
\(N\): The number of maximum iteration, 
\(N1\): Number of new examples generated, 
\(K\): Top-k parameter

**Output:** Test Example Set for Increasing Coverage

1. \(X, Y = \text{Divide}(D)\);
2. Training \textit{AEG} through two equal data domains \(X\) and \(Y\);
3. \(T = \text{Preprocessing}(D)\);
4. Store datasets \(T\) in the processing pool
5. \textbf{while} number of iterations < \(N\) \textbf{do}
6. \(S = \text{HeuristicSelect}(T)\);
7. \(\text{parent} = \text{Sample}(S)\);
8. \textbf{while} number of generation < \(N1\) \textbf{do}
9. \(\text{data} = \text{AEG(parent)}\);
10. \(Fp, Fd = \text{FeatureExtraction(parent, data)}\);
11. \(\text{Similarity = CosineSimilarity(Fp, Fd)}\);
12. \textbf{end while}
13. Selecting top-k examples from all new examples;
14. \textbf{while} number of calculation < \(K\) \textbf{do}
15. \(\text{cov} = \text{DNNFeed(data)}\);
16. \textbf{if} \(\text{IsNewCoverage(cov)}\) \textbf{then}
17. \(\text{Add data to processing pool;}\)
18. \(\text{Setting time priority for data;}\)
19. \textbf{end if}
20. \textbf{end while}

The main flow chart of the \textit{CAGFuzz} approach is shown in Algorithm 1. The input of \textit{CAGFuzz} includes target dataset \(D\), given deep neural network \textit{DNN}, the number of maximum iterations \(N\), the number of adversarial examples \(N1\) generated by each original example and the parameter \(K\) of top-\(k\). The output is the generated test examples that improve the coverage of the target \textit{DNN}. Before the whole fuzzing process, we need to process the dataset. On the one hand, it is divided into two equal data fields (Line 1) to train adversarial example generator \textit{AEG} (Line 2). On the other hand, all examples are pre-processed (Line 3) and stored in the processing pool (Line 4). During each iteration process (Line 5), the original example \textit{parent} is selected from the processing pool according to the time priority (Lines 6-7). Then, each original example \textit{parent} is generated many times (Line 8). For each generation, the adversarial example generator \textit{AEG} is used to mutate the original example \textit{parent} to generate the adversarial example \textit{data} (Line 9). The deep characteristics of the original example \textit{parent} and the adversarial example \textit{data} are extracted separately, and the cosine similarity (Lines 10-11) between them is calculated. Finally, all the adversarial examples generated by original sample are sorted from high to low in similarity, and top-\(k\) of them are selected as the target examples (Line 12). The top-\(k\) adversarial examples are feedback with coverage (Line 15). If the adversarial examples increase the coverage of the target \textit{DNN}, they will be stored in the processing pool and set a time priority (Lines 16-19).

### 3.2 Data Collection and Training AEG

#### 3.2.1 Data Collection

We define the target task of \textit{CAGFuzz} as an image classification problem. Image classification is the core module of most existing DL systems. The first step of \textit{CAGFuzz} is to determine the image classification \textit{DNN} (e.g. LeNet-1, 4, 5) to be tested and the dataset to be classified. The operation of the dataset is divided into two parts. First, all the examples in the dataset are prioritized, and then all the examples are stored in the processing pool as the original example set of the frame. During the process of fuzzing, the fuzzer selects the original example from the processing pool according to the priority to perform the fuzzing operation. Second, the dataset is divided into two uniform groups. According to the domain, it is used as the input of the
cycle generative adversarial network to train the adversarial example generator.

### 3.2.2 Training Adversarial Example Generator

Traditional fuzzers mutate the original examples by flipping bits/bytes, cross-input files and swap blocks to achieve the effect of fuzziness. However, mutation of DNN input using these methods is not achievable or invalid, and may produce a large number of invalid, non-semantic testing examples. At the same time, how to grasp the degree of mutation is also a question for us to think about. If mutation changes very little, the newly generated examples may be almost unchanged. Although this may be meaningful, the possibility of new examples finding DNN errors is very low. On the other hand, if the mutation changes greatly, more defects of DNN may be found. However, the semantics gap between the new generated example and the original example may be also large, that is to say, the new generated example is also invalid.

We propose a new strategy that uses adversarial example generator as mutations. Given an image example \( x \), \( \text{AEG} \) generates an adversarial example \( x' \), and the deep semantics information of \( x' \) is consistent with that of \( x \), but the adversarial perturbations that cannot be observed by human eyes are added. We invert the idea of CycleGAN, add adversarial perturbations to the original example by adversarial loss, and control the perturbations to be invisible to human eyes by cyclic consistency loss.

In Section 3.2.1, we propose to divide the collected data into two groups of data domains evenly. We define these two data domains as data domain \( X \) and data domain \( Y \). Our goal is to use the two data domains as input of the CycleGAN, and to learn mapping functions from each other between the two data domains to train the AEG. By supposing that the set of data domain \( X \) is represented as \( \{x_1, x_2, \ldots, x_n\} \), where \( x_i \) denotes a training example in data domain \( X \). Similarly, the set of data domain \( Y \) denotes \( \{y_1, y_2, \ldots, y_m\} \), where \( y_i \) represents a training example in data domain \( Y \). We define the data distribution of two groups of data domains, where data domain \( X \) is expressed as \( x \sim P_{data}(x) \), and data domain \( Y \) is expressed as \( y \sim P_{data}(y) \). As shown in Fig. 5, the mapping functions between two sets of data domains are defined as \( P : X \rightarrow Y \) and \( Q : Y \rightarrow X \), where \( P \) represents the transformation from data domain \( X \) to data domain \( Y \), and \( Q \) represents the transformation from data domain \( Y \) to data domain \( X \). In addition, there are two adversarial discriminators \( D_x \) and \( D_y \), \( D_x \) distinguishes the original example \( x \) of data domain \( X \) from the one generated by mapping function \( Q \). Similarly, \( D_y \) distinguishes the original example \( y \) of data domain \( Y \) from the adversarial example \( P(x) \) generated by mapping function \( P \).

**Adversarial Loss.** The mapping function between two sets of data domains is designed with loss function. For mapping function \( P \) and corresponding adversarial discriminator \( D_y \), the objective function is defined as follows:

\[
\min_{P} \max_{D} \mathcal{L}_{cycle}(P, Q, X, Y) = E_{y \sim P_{data}(y)}[\log D_{y}(y)] + E_{x \sim P_{data}(x)}[\log (1 - D_{y}(P(x)))]
\]

The function of mapping function \( P \) is to generate adversarial examples \( y' = P(x) \) similar to data domain \( Y \), which can be understood as adding large perturbations with \( Y \) characteristics of data domain to the original example \( x \) of data domain \( X \). At the same time, there is an adversarial discriminator \( D_y \) to distinguish the real examples \( y \) in data domain \( Y \) and the generated adversarial example \( y' \). The objective of the objective function is to minimize the mapping function \( P \) and maximize the adversarial discriminator \( D_y \). Similarly, for the mapping function \( Q \) and the target function set by the adversarial discriminator \( D_x \), the objective function is defined in the following:

\[
\min_{Q} \max_{D} \mathcal{L}_{cycle}(Q, P, X, Y) = E_{x \sim P_{data}(x)}[\log D_{x}(x)] + E_{y \sim P_{data}(y)}[\log (1 - D_{x}(Q(y)))]
\]

**Cycle Consistency Loss.** We can add perturbations to the original example by using the aforementioned adversarial loss function, but the degree of mutation of this perturbation is large, and it is prone to generate invalid adversarial examples. To avoid this problem, we add constraints to the perturbations, and control the degree of mutation through the cycle consistency loss. In this way, the perturbation-resistant human eyes added to the original example are invisible. For example, example \( x \) of data domain \( X \) is generated by mapping function \( P \) to generate adversarial example \( y' \), and then adversarial example \( y' \) is generated by mapping function \( Q \) to generate new adversarial example \( x' \). At this time, the generated adversarial example \( x' \) is similar to the original example \( x \), that is to say, \( x \rightarrow P(x) = y' \rightarrow Q(y') = x' \approx x \). The objective function of the loss function of cyclic consistency is described as follows:

\[
\text{Loss}_{cycle}(P, Q) = E_{x \sim P_{data}(x)}[||Q(P(x)) - x||_1] + E_{y \sim P_{data}(y)}[||P(Q(y)) - y||_1]
\]

The overall structure of the network has two generators: \( P \) and \( Q \), and two discriminator networks \( D_x \) and \( D_y \). The whole network is a dual structure. We combine two generators with opposite functions into our adversarial example generator. The effect picture of AEG is shown in Fig. 6, we show that the adversarial example generation process has 12 groups of pictures of different categories. In each picture, the leftmost column is the original example, the middle column is the transformed example of the original example,
3.3 Adversarial Example Generation

3.3.1 Example Priority

The priority of the example determines which kind of examples should be selected next time. We choose a probabilistic selection strategy based on the time of adding examples to the processing pool. We adopt a meta-heuristic formula with faster selection speed. The probability calculation formula is described as follows: \( h(b_i, t) = \frac{e^{t_i - t}}{\sum b_j e^{t_j - t}} \), where \( h(b_i, t) \) represents the probability of selecting example \( b_i \) at time \( t \), and \( t_i \) represents the time when example \( b_i \) joins the processing pool.

This priority can be understood as that the most recently sampled examples are more likely to generate useful new neuron coverage when mutating to adversarial examples. However, when time passes, the advantage will gradually diminish.

3.3.2 Feature Extraction

To ensure the meaning of the generated adversarial examples as much as possible, we adopt the strategy of extracting the semantics features of the original examples and adversarial examples and controlling their differences within a certain range. The deep feature recognition ability and semantics expression ability extracted by CNN are stronger. Consequently, we select VGG-19 network to extract the semantic features of examples. The features in VGG-19 model are extracted according to the hierarchy. Compared with the high-level features, the low-level features are unlikely to contain rich semantics information.

The features extracted from VGG-19 network model can represent images better than traditional image features. It also shows that the deeper the layer of convolution network, the more parameters in the network, and the better the image can be expressed. We fuse the output of the last full connection layer (Fc8 layer in Fig. 3) as eigenvectors, and the dimension of eigenvectors is 4096.

3.3.3 Cosine Similarity Computation

During the mutation process, AEG generates multiple adversarial examples for each original example. We assume that the original example is \( a \), and the set of all adversarial examples is \( T = \{a_1, a_2, ..., a_n\} \) which extracts the semantics feature vectors for the original example and all the confrontational examples by the feature extraction method mentioned above. The dimension of each feature vector is 4096. Supposing that the eigenvector corresponding to the original example \( a \) is \( X = [x_1, x_2, ..., x_n]_{n=4096} \), and the corresponding eigenvector of an adversarial example is \( a_i \) is \( Y = [y_1, y_2, ..., y_n]_{n=4096} \), where \( a_i \in T \). Cosine similarity is used to measure the difference between each adversarial example and the original example. The formula is described
as follows:

$$COS(X, Y) = \frac{X \cdot Y}{||X|| \times ||Y||} = \frac{\sum_{i=1}^{n}(x_i \times y_i)}{\sqrt{\sum_{i=1}^{n} x_i^2} \times \sqrt{\sum_{i=1}^{n} y_i^2}}$$

(5)

where $x_i$ and $y_i$ correspond to each dimension of eigenvector $X$ and $Y$.

To control the size and improve the mutation quality of adversarial examples, we select the top-$k$ adversarial examples sorted from high to low cosine similarity as eligible examples to continue the follow-up steps. In our approach, we set $K = 5$, that is to say, we select the five adversarial examples with the highest cosine similarity for neuron coverage.

3.4 DNN Feedback

Without coverage as a guiding condition, the adversarial examples generated by AEG are not purposeful. Consequently it is impossible to know whether the adversarial examples are effective or not. If the generated adversarial examples cannot bring new coverage information to the DNN to be tested, these adversarial examples can only simply expand the dataset, but cannot effectively detect the potential defects of DNN. To make matters worse, mutations in these adversarial examples may bury other meaningful examples in a fuzzy queue, significantly reducing the fuzzing effect. Therefore, neuron coverage feedback is used to determine whether the newly generated adversarial examples should be placed in the processing pool for further mutation.

After each round of generation and similarity screening, all valid adversarial examples are used as the input of DNN to be tested for neuron coverage analysis. If the adversarial examples generate new neuron coverage information, we will set priority for the adversarial examples and store it in the processing pool for further mutation. For example, a DNN for image classification consists of 100 neurons. 32 neurons are activated when the original example is input into the network, and 35 neurons are activated when the adversarial example is input into the network. Consequently, we say that the adversarial example brings new coverage information.

4 EXPERIMENTAL EVALUATION

In this section, we perform a set of dedicated experiments to validate CAGFuzz. Section 4.1 proposes the research questions. Section 4.2 describes the experimental design. Section 4.3 provides the experimental results and Section 4.4 discusses some threats to validity.

4.1 Research Questions

We use a variety of datasets and the corresponding image classification models to carry out a series of experiments to validate CAGFuzz. The purpose of the experiments is designed to explore the following four main research questions:

RQ1: Could the generated adversarial examples based on data have stronger generalization ability than those based on models?

RQ2: Could CAGFuzz improve the neuron coverage in the target network?

RQ3: Could CAGFuzz find potential defects in the target network?

RQ4: Could the accuracy and the robustness of the target network be improved by adding adversarial examples to the training set?

To discover potential defects of target network and expand effective examples for data sets, the CAGFuzz approach mainly generates adversarial examples for DNNs to be tested. Therefore, we designed RQ1 to explore whether the examples generated based on data have better generalization ability than those based on models. For neuron coverage, we designed RQ2 to explore whether CAGFuzz can effectively generate test examples with more coverage information for target DNNs. We designed RQ3 to study whether CAGFuzz can discover more hidden defects in target DNNs. RQ4 is designed to explore whether adding the adversarial examples generated by CAGFuzz to the training set can significantly improve the accuracy of target DNNs.

4.2 Experimental Design

4.2.1 Experimental Environment

The experiments have been performed on Linux machines. The description of the hardware and software environments of the experiments is shown in Table 1.

| Name               | Standard               |
|--------------------|------------------------|
| CPU                | Xeon Silver 4108       |
| GPU                | NVIDIA Quadro P4000    |
| RAM                | 32G                    |
| System             | Ubuntu 16.04           |
| Programming environment | Python               |
| Deep learning open source framework | Tensorflow1.12 |

4.2.2 DataSets and Corresponding DNN Models

For research purpose, we adopt two popular and commonly used datasets with different types of data: MNIST [21] and CIFAR-10 [22]. At the same time, we have learned and trained several popular DNN models for each dataset, which have been widely used by scientific researchers. In Table 2 we provide an informative summary of these datasets and the corresponding DNN models. All the evaluated DNN models are either pre-trained (i.e., we use the common weights in previous researchers’ papers) or trained according to standards by using common datasets and public network structures.

MNIST [21] is a large handwritten digital dataset containing $28 \times 28 \times 1$ pixels of images with class labels ranging from 0 to 9. The dataset contains 60,000 training examples and 10,000 test examples. We construct three different kinds of neural networks based on LeNet family, namely LeNet-1, LeNet-4 and LeNet-5.
CIFAR-10 [22] is a set of general image classification images, including $32 \times 32 \times 3$ pixel three-channel images, including ten different kinds of pictures (such as aircraft, cats, trucks, etc.). The dataset contains 50,000 training examples and 10,000 test examples. Due to the large amount of data and high complexity of CIFAR-10, its classification task is more difficult than MNIST. To obtain the competitive performance of CIFAR-10, we choose three famous DNN models VGG-16, VGG-19, and ResNet-20 as the targeted models.

| DataSet | DataSet Description | Model  | Test acc(%) |
|---------|----------------------|--------|-------------|
| MNIST   | Hand written digits from 0 to 9 | LeNet-1 | 98.25 |
|         |                      | LeNet-4 | 98.75 |
|         |                      | LeNet-5 | 98.63 |
| CIFAR-10 | 10 class general image | VGG-16 | 86.84 |
|         |                      | VGG-19 | 77.26 |
|         |                      | ResNet-20 | 82.86 |

4.2.3 Contrast Approaches

As surveyed in [31], there is only several open-source tools in testing DL applications. Some released tools, such as Themis [4], mltest [3] and torchtest [2] do not focus on generating adversarial examples. Thus, to measure the ability of CAGFuzz, we selected the following three representative DL testing approaches proposed recently in the literature as our contrast approaches, respectively:

- **FGSM [32]** (Fast Gradient Sign Method). A typical approach generates adversarial examples from the perspective of model. Consequently, we use FGSM to generate adversarial examples to compare with CAGFuzz, and verify that the generated adversarial examples based on data has more generalization ability than those based models.

- **DeepHunter [13]**. An automated fuzz testing framework for hunting potential defects of general-purpose DNNs. DeepHunter performs metamorphic mutation to generate new semantically preserved tests, and leverages multiple plug-able coverage criteria as feedback to guide the test generation from different perspectives.

- **DeepXplore [10]**. The first white box system for systematically testing DL systems and automatically identify erroneous behaviors without manual labels. DeepXplore performs gradient ascent to solve a joint optimization problem that maximizes both neuron coverage and the number of potentially erroneous behaviors.

Since there is no open source version of DeepHunter, we choose the data in [13] as the comparative experimental data, and DeepHunter does not mention the accuracy of the model. Consequently, CAGFuzz is compared with DeepHunter and DeepXplore in neuron coverage and only compared with DeepXplore in model accuracy improvement.

4.3 Experimental Results

4.3.1 Training of Target DNNs

To ensure the correctness and validate the evaluation results of the experiments, we carefully select several popular DNN models with competitive performance for each dataset. These DNN models have been proven to be standard in previous researchers’ experiments. In our approach, we closely follow the common machine learning training practices and guidelines, and set the learning rate for training DNN model. During the initialization process of DNN model learning rate, if the learning rate is too high, the weight of the model will increase rapidly, which will have a negative impact on the training of the whole model. Consequently, the learning rate is set to a smaller value at the beginning. For the three LeNet models of the MNIST dataset, we set the learning rate as 0.0005 based on experiences because of the deeper network layers and the more complex model. In addition, we initially set the epoch for each model to 100 training times. The LeNet model works well, but when we train VGG-16 network, we find that the accuracy of the model is basically stable after 50 training epochs, as shown in Fig. 7. Therefore, during the process of training VGG-19 network and the subsequent retraining model stage, we set the training epochs to 50, which can save a lot of computing resources and space-time costs. During the process of training ResNet-20 model, we set up a three-stage adaptive learning rate. When $epoch < 20$, we set the learning rate as $1e^{-3}$. When $20 < epoch < 50$, we set the learning rate as $1e^{-4}$. When $epoch > 50$, we set the learning rate as $1e^{-5}$.

In Fig. 8, we show the training loss, training accuracy, validation loss and validation accuracy of each model. From the figure, we can see, during the training process of LeNet-5, with the increase of training times, the loss value of the model gradually decreases, and the accuracy is getting higher and higher. This shows that with the increase of training times, the model can fit the data well, and the model can accurately classify the dataset. We follow the criterion of machine learning, and then choose the competitive DNN models as the research object for the fuzzy test under the condition of fitting.

4.3.2 Generalization Ability

To answer RQ1, we compare CAGFuzz with existing model-based approach FGSM. We choose MNIST data set as the sampling set, and sampling 10 examples for each class in the training set and 4 examples for each class in the test set.

Based on the LeNet-1 model, we use FGSM to generate an adversarial example for each of the 10 examples in the training set, and also use AEG to generate an adversarial example for each training example. First, the original data set is used to train and test the LeNet-1 model. We set the
epoch value as 50 and the learning rate as 0.05. Then, the adversarial examples generated by CAGFuzz and FGSM are added to the training set to retrain LeNet-1 with the same parameters. Finally, the above two steps are repeated, but the model is replaced by LeNet-4 or LeNet-5.

Similar to generating adversarial examples based on LeNet-1, we perform the same experiment on LeNet-4 and LeNet-5. Because of the uncertainty during the model training process, we train the model repeatedly 5 times in the same setting, and take the average of these results as the final accuracy of our experiments. Table 3 shows the accuracy of the three models on the original data set, adversarial examples generated based on LeNet-1, 4, 5 model and adversarial examples generated based on CAGFuzz. From the table, it can be seen that the accuracy of the adversarial examples generated by FGSM based on the specific model is improved higher than that of other models. Taking the adversarial examples generated based on LeNet-1 as an example, these adversarial examples improve the accuracy of LeNet-1 by 19.6%, while only 6.3% and 14.3% are improved for LeNet-4 and LeNet-5, respectively. However, the adversarial examples generated by CAGFuzz show the same improvement effect on the three models, the accuracy of the three models is improved by 23.05%, 15.01% and 22.6% respectively. The average accuracy of the model is higher than that of FGSM after the model is retrained by adversarial examples.

It can be seen from the figure, the neuron coverage is improved in all the models, but the promotion effect is fluctuated in different models. When the threshold is set to 0.2, the neuron coverage of LeNet-1 model increases from 26.90% to 38.46%. Under the same threshold setting, the neuron coverage of VGG model and ResNet model with deep network layer and large number of neurons improved less.

4.3.3 Neuron Coverage

To answer RQ2, we use the training data set of each model as the input set to calculate the original neural coverage, and the generated adversarial example set as the input set to calculate the neural coverage of CAGFuzz. An important parameter for calculating the neuron coverage is the user-defined activation threshold. If the output value of a neuron is higher than this threshold, the neuron is counted as covered. We use the same data set and model to compare the changes in neuron coverage before and after using CAGFuzz. For the threshold parameters, we first set the threshold values to 0 and 0.75, as shown in [10]. For a more complete comparison, we also used two other parameter sets (0.2 and 0.5). Fig. 9 and Fig. 10 show that, under different activation thresholds, the model change in neuron coverage before and after the use of CAGFuzz based on MNIST data set and CIFAR-10 data set. As can be seen from the figure, the neuron coverage is improved in all the models, but the promotion effect is fluctuated in different models. When the threshold is set to 0.2, the neuron coverage of LeNet-1 model increases from 26.90% to 38.46%. Under the same threshold setting, the neuron coverage of VGG model and ResNet model with deep network layer and large number of neurons improved less.

Obviously, the adversarial examples generated by AEG can effectively improve the neuron coverage of target DNNs. To further validate the effectiveness of CAGFuzz in improving neuron coverage, we also compare it with DeepHunter [13] and DeepXplore [10]. Since DeepHunter does not mention the activation threshold they used, we chose a threshold similar to their results (threshold=0.2). Table 4 lists the original neuron coverage of each model and the neuron coverage using the fuzzy test method (DeepHunter does not use the VGG-19 model and the data is default). It can be seen from the table that CAGFuzz is better than DeepHunter and DeepXplore in LeNet models. However, in VGG model and ResNet model, the effect of CAGFuzz is less obviously. Different from DeepHunter's eight mutation methods to generate examples, there is a big gap between the generated examples and the original examples. The depth feature constraint is used in the AEG generated adversarial examples. The adversarial examples only add small perturbations to the original examples, so the neuron coverage of the model with deeper layers is not significantly improved. However, after the training of these adversarial examples, the robustness and the accuracy of the model is significantly improved. In general, it can be concluded that the neuron coverage of models with deeper layers and larger number neurons is less affected by adversarial examples.

4.3.4 Error Behavior Discovery

To answer RQ3, we sample correctly classified samples from the test set of each dataset. Based on these correctly classified examples, we generated adversarial examples for each example through the AEG of each dataset. The examples we selected are all positive examples with correct classification. We can confirm that all the generated adversarial examples should also be classified correctly, because the depth semantics information of the adversarial examples
and the original examples are consistent. The “positive examples” generated by AEG are input into the corresponding classifier model for classification. If there are errors or classification errors, a potential defect of the classification model can be found. We define the original correct example as $Image_{orig}$ and the corresponding adversarial example as $Image_{adv} = \{Image_1, Image_2, ..., Image_{10}\}$. The original example $Image_{orig}$ is classified correctly in the target DNN model, consequently $Image_i$ should also be classified correctly, where $Image_i \in Image_{adv}$. If the $Image_i$ classification of an adversarial example is wrong, we consider this to be an error behavior of the target DNN.
We choose a quantitative method to evaluate the effectiveness of CAGFuzz in detecting erroneous behaviors in different models. As mentioned above, we generate 50,000 adversarial examples for each dataset. Table 5 shows the number of erroneous behaviors found by different DNN models under the guidance of neuron coverage. In addition, we also list the number of errors found by DeepHunter in each model for comparison. Because DeepHunter does not experiment on VGG-19 model, the experimental data of VGG-19 model is missing in the table. Therefore, we neglect the VGG-19 model when we count the total number of erroneous behaviors found in the experiments.

Evidently, except for the LeNet-1 model, CAGFuzz has found more potential errors in DNN models than DeepHunter. Before DNN model is deployed to actual production, it is very important to find more DNN model errors and improve them. Although such manual investigation is, by definition, subjective and approximate, all the authors have reviewed the images and agreed on the false positives.

### TABLE 5
Number of erroneous behaviors reported by CAGFuzz and DeepHunter across all tested models.

| DNN Models | CAGFuzz(unit in 1k) | DeepHunter(unit in 1k) |
|------------|---------------------|------------------------|
| LeNet-1    | 5.09                | 6.9                    |
| LeNet-4    | 6.41                | 4.7                    |
| LeNet-5    | 5.23                | 2.9                    |
| VGG-16     | 8.79                | 2.2                    |
| VGG-19     | 11.97               | -                      |
| ResNet-20  | 9.56                | 0                      |
| SUM        | 35.08               | 16.7                   |

### 4.3.5 Accuracy and Robustness

To answer RQ4, we add adversarial examples generated by CAGFuzz to the training set to retrain the DNN model and measure whether it can improve the accuracy of the target DNN. We select MNIST and CIAR-10 data sets as our experimental data sets, and select LeNet-1, 4, 5, 6 five three DNN models and VGG-16 and VGG-19 models as experimental models. We retrain the DNN model by mixing 65% of the adversarial example set and the original training set, and then validate the DNN model with the remaining 35% of the adversarial example set and the original test set on the original model and the retraining model. The comparisons of the original accuracy and the retraining accuracy of all models are shown in Fig. 11. From Fig. 11(a) we can see that the robustness of the original model is very poor. After adversarial examples are added into the test set, the accuracy of the model decreases obviously. For example, the accuracy of LeNet-5 model decreases from 98.63% to 93.02% and from 5.69% on the original basis. In the VGG-19 model, the accuracy of the model decreases from 77.26% to 75.86%.

Fig. 11(b) shows that we can clearly see that the accuracy of the model has been greatly improved after the re-training of the adversarial examples, especially for the VGG model with deeper layers. For example, from the figure, we can see that the accuracy of the VGG-19 network has increased from 75.86% to 95.96%, and increased by 26.5%. In general, we can see that CAGFuzz can not only improve the robustness of the model, but also improve the accuracy of the model, especially for the model with deeper network layer.

In the experiments, we further analyze the accuracy of the retraining model and the original model during the training process, and evaluate the validity of the adversarial examples generated by CAGFuzz from the change of the validation accuracy. Fig. 12 shows the changes of validation accuracy of different models during training. The original structure parameters and learning rate of each model are kept unchanged, and the new data set we reconstituted is
used for retraining. During the training process, the validation accuracy and the original validation accuracy of the same epoch are compared. It can be found that under the same epoch, the validation accuracy of the retraining model is higher than that of the original model, and the convergence speed of the retraining model is faster. Moreover, it can also be found from the figure that the retraining model is more stable and has a smaller change range during the training process.

In addition, we can see that the trend of the retraining model is basically consistent with the original model, which shows that the accuracy of the model can be greatly improved without affecting the internal structure and logic of the model. For example, in Fig. 12(d), the accuracy of the original model drops suddenly when epoch = 6, and the retraining model also continues this change. In Fig. 12(f), the original model presents a three-stage upgrade, which is reflected in the retraining model at the same time.

To further validate this approach, we train LeNet-1, LeNet-4 and LeNet-5 with 60,000 original images. We further expand the training data by adding the same number of new generated examples, and train DNNs by 5 epochs. Our experiment results shown in Fig. 13 are compared with DeepXplore [10]. It can be found that CAGFuzz has a low initial accuracy when the model is retrained. With the increase of epoch, the accuracy of the model increases rapidly, and the final accuracy is higher than that of DeepXplore.

### 4.3.6 Answers to Research Questions

We designed a set of experiments to obtain the answers to the four research questions raised in Section 4.1. Now, based on our experimental results, we give the corresponding answers to these questions.

- **Answer 1:** Taking MNIST data set and three LeNet models as examples, we prove that adversarial examples generated based on model (such as FGSM) only improve the accuracy of this special model better, and the improvement of other models is limited. On the contrary, CAGFuzz can generate adversarial examples based on data, which can improve the accuracy of all the models to the same degree. That is to say, it has better generalization ability.

- **Answer 2:** CAGFuzz can effectively generate adversarial examples and these adversarial examples can improve neuron coverage for the target DNN. Due to the depth feature constraint, the neuron coverage of the adversarial examples to the model with deeper layers is improved relatively. However, the robustness and accuracy of the model are improved obviously.

- **Answer 3:** With neuron coverage guided adversarial examples, CAGFuzz successfully detects more than 6,000 erroneous behavior as predicted by every DNN models with a low false positive rate.

- **Answer 4:** The accuracy of a DNN can be improved by retraining the DNN with adversarial examples generated by CAGFuzz. The accuracy of the best
model is improved from the original 86.72% to 97.25%, with an improvement of 12.14%.

4.4 Threats to Validity

In the following, we describe the main threats to validity of our approach in detail.

Internal validity: During the experimental process, the data set used to train AEG is manually divided into two data domains, which may lead to subjective differences. To mitigate this threat, after the data domain is divided, we asked three observers to randomly exchange the examples of the two data domains, and three selected observers complete independently. In addition, we pre-train with the initial data domains and then retrain with the data domains adjusted by other observers.

External validity: During the experimental process, the classification of experimental data set is limited, which may lead to the reduction of the generality of the approach to a certain extent. To solve this problem, we use a cross-data set approach to validate the generalization performance of the approach.

Conclusion validity: According to the designed three problems, we can validate our approach. To further ensure the validity of the conclusion, we validated the conclusion through the valid data sets and models from other researchers, and reached the same conclusion as the standard data set.

5 Related work

In this section, we review the most relevant work in three aspects. Section 5.1 introduces the adversarial deep learning and some adversarial examples generation approaches. Section 5.2 elaborates coverage-guided fuzz testing of traditional software. Section 5.3 introduces the state-of-the-art testing approaches of DL systems.

5.1 Adversarial Deep Learning

A large number of recent research has shown that adversarial examples with small perturbations poses a great threat to the security and robustness of DL systems [17], [33], [34]. Small perturbations to the input images can fool the whole DL systems, and the input image is initially classified correctly by the DL systems. Although in human eyes, the modified adversarial example is obviously indistinguishable from the original example.

Goodfellow et al. [32] proposed FGSM (Fast Gradient Sign Method) which can craft adversarial examples using loss function \( J(\theta, x, y) \) with respect to the input feature vector, where \( \theta \) denotes the model parameters, \( x \) is the input, and \( y \) is the output label of \( x \). The adversarial example is generated as: \( x' = x + \epsilon \text{sign}(\nabla_x J(\theta, x, y)) \).

Papernot et al. [35] proposed JSMA (Jacobian-based Saliency Map Attack). For an input \( x \) and a neural network \( N \), the output of class \( j \) is denoted as \( N_j(x) \). To achieve a target misclassification class \( t \), \( N_t(x) \) is increased while the probabilities \( N_j(x) \) of all other classes \( j \neq t \) decrease, until \( t = \arg \max_j N_j(x) \).

Kurakin et al. [36] proposed BIM (Basic Iterative Method). The method applies adversarial noise \( \eta \) many times iteratively with a small parameter \( \epsilon \), rather than one \( \epsilon \) with one \( \eta \) at a time, which gives a recursive formula: \( x_0 = x \) and \( x_j = \text{clip}_{\epsilon, \eta}(x_{j-1} + \epsilon \text{sign}(\nabla_x J(\theta, x_{j-1}, y))) \), where \( \text{clip}_{\epsilon, \eta}(\cdot) \) denotes a clipping of the values of the adversarial sample such that they are within an \( \epsilon \)-neighborhood of the original input \( x \).

Carlini et al. [37] proposed CW (Carlini and Wagner Attacks), a new optimization-based attack technique which is arguably the most effective in terms of the adversarial success rates achieved with minimal perturbation. In principle, the CW attack is to approximate the solution to the following optimization problem: \( \arg \min_{x'} \lambda L(x, x') - J(\theta, x', y) \), where \( L \) is a loss function to measure the distance between the prediction and the ground truth, and the constant \( \lambda \) is to balance the two loss contributions.

In summary, all these approaches focus on generating adversarial examples. However, they only attempt to find a specific kind of error behavior, that is, to force incorrect prediction by adding minimum noise to a given input. In this way, these approaches are DNN dependent, and the generated adversarial examples are not universal. In contrast, our approach does not depend on a specific DNN, and uses the distribution of two sets of data domains to learn from each other, so as to add small perturbations to the original examples.
5.2 Coverage-Guided Fuzz Testing

Coverage-guided fuzzy testing (CGF) is a mature defect and vulnerability detection technology. A typical CGF usually performs the following loops: 1) selecting seeds from the seed pool; 2) mutating seeds for a certain number of times to generate new tests using bit/byte flip, block substitution, and crossover of two seed files; 3) running the target program for the newly generated input and recording the execution trajectory; 4) if the detection is made in example of collapse, the fault seeds are reported and the interesting seeds covered with new traces are stored in the seed pool.

Superion, conceptually extends LangFuzz with coverage-guided, the seeds of structural mutation that increase coverage are retained to further fuzzing. While Superion works well for highly structured inputs such as XML and JavaScript, AFLSMART’s variation operators better support block based file formats such as image and audio files.

Zest and libprotobuf mutator have been proposed to improve the mutation quality by providing structure aware mutation strategies. Zest compiles the syntax specification into a fuzzier driver stub for the coverage-guided greybox fuzzier. This fuzzier driver translates byte-level mutations of LibFuzzer into structural mutations of the fuzzier target.

NEZHA is used to focus on inputs that are more likely to trigger logic errors by using behavioral asymmetries between test programs. The behavior consistency between different implementations acts as Oracle to detect functional defects.

Due to the inherent difference between DL systems and traditional software, traditional CGF cannot be directly applied to DL systems. In our approach, CGF is adopted to be suitable for DL systems. The state-of-the-art CGF mainly consists of three parts: mutation, feedback guidance, and fuzzing strategy, in which we replace mutation with the adversarial example generator trained by CycleGAN. In the feedback part, neuron coverage is used as the guideline. In the fuzzy strategy part, because the test is basically input by the same format of images, the adversarial examples generated with higher coverage are selected and put into the processing pool to maximize the neuron coverage of the target DL systems.

5.3 Testing of DL Systems

In traditional software testing, the main idea of evaluating machine learning systems and deep learning systems is to randomly extract test examples from manually labeled datasets and hoc simulations to measure their accuracy. In some special cases, such as autopilot, special non-guided simulations are used. However, without understanding the internal mechanism of models, such black-box test paradigms cannot find different situations that may lead to unexpected behavior.

DeepXplore proposes a white-box differential testing technique for generating test inputs that may trigger inconsistencies between different DNNs, which may identify incorrect behavior. For the first time, this method introduced concept of neuron coverage as a metric of DL testing. At the same time, it requires multiple DL systems with functions similar to cross-reference prediction to avoid manual checking. However, cross-references have scalability and difficulties in finding DL-like systems. In contrast, our approach, CAGFuzz, uses neuron coverage to guide adversarial examples generation in a single DNN, and uses the original network to identify erroneous behavior without requiring multiple DNNs.

DeepHunter performs mutations to generate new semantic retention tests, and uses multiple pluggable coverage criteria as feedback to guide test generation from different perspectives. Similar to traditional coverage-guided fuzzy (CGF) testing, DeepHunter uses random mutations to generate new test examples. Although there is a screening mechanism to filter invalid use examples, it still wastes time and computing resources. DeepHunter uses the methods of changing contrast, image scaling and image translation to mutate the image. It only changes the visual information of the image, cannot express the deep semantic information of the image, and cannot well reflect the adversarial perturbations.

The validity of DLFuzz shows that it is feasible to apply the fuzzy knowledge to DL testing, which can greatly improve the performance of existing DL testing technologies such as DeepXplore. Gradient-based optimization problem solution ensures simple deployment and high efficiency of the framework. The mechanism of seed maintenance provides different directions and more space for improving the coverage of neurons.

In addition, many testing approaches for traditional software have also been adopted and applied to testing DL systems, such as statement, branch, condition and MC/DC coverage. Furthermore, various forms of neuron coverage have been defined, and are demonstrated as important metrics to guide test generation.

6 Conclusions and Suggestions for Future Work

We design and implement CAGFuzz, a coverage-guided adversarial generative fuzzing testing approach. CAGFuzz trains an adversarial example generator for a specified dataset. It generates adversarial examples for target DNN by iteratively taking original examples, generating adversarial examples and feedback of coverage rate, and finds potential defects in the development and deployment phase of DNN. We have done a lot of experiments to prove the effectiveness of CAGFuzz in promoting DNN coverage, discovering potential errors in DNN and improving model accuracy. The goal of CAGFuzz is to maximize the neuron coverage and the number of potential erroneous behaviors. The experimental results show that CAGFuzz can detect thousands of erroneous behaviors in advanced DNN models, which are trained on publicly popular datasets.

Several directions for future work are possible.

- At present, we only use neuron coverage to guide the generation of adversarial examples. Neuron coverage may not cover all the logic of DNN effectively. In the future, we can use multidimensional coverage feedback to improve the information that adversarial examples can cover.
• CAGFuzz adds perturbation information to the original example by mapping between two data domains. These perturbations are uncontrollable. In the future, the perturbation information can be added to the original sample by feature control.

• This paper mainly studies image examples, and how to train effective adversarial example generator for other input forms, such as text information and voice information, is also a meaningful direction.

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