DeepGini: Prioritizing Massive Tests to Reduce Labeling Cost
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ABSTRACT
Deep neural network (DNN) based systems have been deployed to assist various tasks, including many safety-critical scenarios such as autonomous driving and medical image diagnostics. In company with the DNN-based systems’ fantastic accuracy on the well-defined tasks, these systems could also exhibit incorrect behaviors and thus severe accidents and losses. Therefore, beyond the conventional accuracy-based evaluation, the testing method that can assist developers in detecting incorrect behaviors in the earlier stage is critical for quality assurance of these systems. However, given the fact that automated oracle is often not available, testing DNN-based system usually requires prohibitively expensive human efforts to label the testing data. In this paper, to reduce the efforts in labeling the testing data of DNN-based systems, we propose DeepGini, a test prioritization technique for assisting developers in identifying the tests that can reveal the incorrect behavior. DeepGini is designed based on a statistical perspective of DNN, which allows us to transform the problem of measuring the likelihood of misclassification to the problem of measuring the impurity of data set. To validate our technique, we conduct an extensive empirical study on four popular datasets. The experiment results show that DeepGini outperforms the neuron-coverage-based test prioritization in terms of both efficacy and efficiency.

KEYWORDS
Deep learning, neural networks, test case prioritization.

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1 INTRODUCTION
We are entering the era of deep learning, which has been widely adopted in many areas. Famous applications of deep learning include image classification [10], autonomous driving [2], speech recognition [36], playing games [29], and so on. Although for the well-defined tasks, such as in the case of Go [29], deep learning has achieved or even surpassed the human-level capability, it still has many issues on reliability and quality that could cause significant loss as in the accidents caused by the self-driving car of Google and Tesla.1, 2

However, almost all existing studies focus only on pursuing high accuracy of DL systems as a performance criterion, only a little work centered on assist software tester in detecting incorrect behaviors of these DNN-based systems. On the other hand, different from the conventional software systems that depend on developers manually define many conditional branches to form the system logic, DNN-based systems are built upon a rich data-driven programming paradigm that employs plenty of labeled data to train a set of neurons to construct the internal system logic. Given the inherent nature of the DNN, adequacy of testing data becomes critical for detecting incorrect behaviors of DNN-based systems.

Like the testing techniques for conventional software, testing deep neural networks (DNN) also faces the problem that automated oracle is often unavailable. Thus, one of the primary challenges for the tester of DNN-based systems is to label the inputs. To test DNN-based systems, software engineers have to invest a lot of manpower to label the tests, which is prohibitively expensive. In the past decade, to obtain the training data and testing data for building the DNN models, researchers and practitioners have invested many efforts and resources. For example, building the ImageNet 3, which is considered to be the largest visual recognition dataset containing more than 20,000 categories and millions labeled data, costs 49k workers from 167 countries more than 9 years. Nevertheless, specifically for the testing of DNN-based systems, software tester can focus on these tests that can cause the system to behave incorrectly because diagnosing failed tests can provide insights into various problems in a software program [26]. This fact naturally motivates us to propose a prioritization technique to assist testers in identifying the tests causing misclassification in the earlier stage. In this manner, we can obtain maximum benefit from human efforts, even if the labeling process is prematurely halted at some arbitrary point due to the resource limit.

To each the same goal, many test prioritization techniques have been proposed for the conventional software systems [7, 26, 37]. In these technique, code coverage is employed as the metric to guide the prioritizing procedure. Unfortunately, for DNN-based systems, although several neuron-coverage criteria for DNNs have been proposed [17, 20], the aforementioned coverage-based methods are not effective as expected for DNN testing, due to some new challenges. First, some coverage criteria cannot distinguish the fault detection capability of different tests. Thus, we cannot prioritize them effectively. For example, given a DNN, every test input of the DNN have the same top-$k$ neuron coverage rate [17]. As a result, the coverage-total prioritization method becomes meaningless using this coverage criterion. Second, for most of these coverage criteria,
We compare the effectiveness of prioritization with the two kinds of weakness. First, this issue is shared with all coverage-based test methods, as they also need to run tests to obtain coverage rates. However, we argue that this is not a significant problem for our approach at least as scalable as coverage-total approaches and much more effective test prioritization method is presented for DNN testing. Thus, our approach is immune to adversarial attacks.

In summary, our main contribution is three-fold:

- We propose a metric called DeepGini for measuring a test’s likelihood of being misclassified. Using this metric, an effective test prioritization method is presented for DNN testing.
- We demonstrate the weaknesses of using existing coverage criteria to guide test prioritization for a deep learning system.
- We extensively evaluate our method and demonstrate that it is much more effective than coverage-based methods.

2 BACKGROUND

In this section, we introduce the basic knowledge of DNN and the advances of the criteria for measuring the DNN testing adequacy.

2.1 Deep Neural Networks

Deep neural network (DNN) is the core of a deep learning system. As shown in Figure 1, a DNN consists of multiple layers, i.e., an input layer, an output layer, and one or more hidden layers. Each layer is made up of a series of neurons. The neurons from different layers are interconnected by weighted edges. Each neuron is a computing unit that applies an activation function on its inputs and the weights of the incoming edges. The computed result is passed to the next layer through the edges. The weights of the edges are not specified directly by the software developers, but automatically learned by a training process with a large set of labeled training data. After training, a DNN then can be used to automatically classify an input object, e.g., an image with an animal, into its corresponding class, e.g., the animal species.

Suppose we have a DNN that can classify objects into N classes. Given an input, the DNN will output a vector of N values, e.g.,
\((v_1, v_2, \cdots, v_N)\), each of which represents how much the system thinks the input corresponds to each class. Apparently, using a softmax function [6], it is easy to normalize this vector to \(\langle p_1, p_2, \cdots, p_N \rangle \) where \(\xi_{i=1}^{N} p_i = 1\), and \(p_i\) indicates the probability that an input belongs to the \(i\)th class. From now on, with no loss of generality, we assume the output vector of a DNN is a vector of probabilities as described above.

2.2 Coverage Criteria for DNN Testing
Considering that a series of coverage criteria have been proposed for DNN testing [17, 20], in this section, we briefly introduce them.

**Neuron Activation Coverage (NAC(\(k\)))** [20]. NAC(\(k\)) is proposed based on the assumption that higher activation coverage implies that more states of a DNN could be explored. Thus we have more opportunities to find defects. The parameter \(k\) of this coverage criterion is defined by users and specifies how a neuron in a DNN can be counted as covered. That is, if the output of a neuron is larger than \(k\), then this neuron will be counted as covered. The rate of NAC(\(k\)) for a test is defined as the ratio of the number of covered neurons and the total number of neurons.

**\(k\)-Multisection Neuron Coverage (KMNC(\(k\)))** [17]. Suppose that the output of a neuron \(o\) is located in an interval \([low_o, high_o]\), where \(low_o\) and \(high_o\) are recorded in the training process. To use this coverage criterion, the interval \([low_o, high_o]\) is divided into \(k\) equal sections, and our goal is to cover all the sections of each neuron. We say a section is covered by a test if and only if the neuron output is located in the section when the DNN is run against the test. The rate of KMNC(\(k\)) for a test is defined as the ratio of the number of covered sections and the total number of sections. Here, the total number of sections is equal to \(k\) times the total number of neurons.

In most cases, a single test covers a section in \([low_o, high_o]\) for each neuron. Only a tiny number of tests do not cover a section in the interval, but cover the boundaries, i.e., \((-\infty, low_o]\) and \([high_o, +\infty)\). Thus, almost all single tests have the same coverage rate of KMNC(\(k\)). Even with a different coverage rate, the difference is very small and negligible. Therefore, CTM does work using this coverage metric.

**Neuron Boundary Coverage (NBC(\(k\)))** [17]. Different from KMNC(\(k\)), NBC(\(k\)) does not aim to cover all sections in \([low_o, high_o]\). Instead, it targets to cover the boundaries, i.e., \((-\infty, low_o]\) and \([high_o, +\infty)\). Using this coverage criterion, we can expect to cover more corner cases. In practice, it is not necessary to directly use \(low_o\) and \(high_o\) as the boundaries. Instead, \(low_o-\sigma k \) and \(high_o+\sigma k\) can be used. Here, \(\sigma\) is the standard deviation of the outputs of a neuron recorded in the training process. \(k\) is a user-defined parameter. The rate of NBC(\(k\)) for a test is defined as the ratio of the number of covered boundaries and the total number of boundaries. Since each neuron has one upper bound and one lower bound, the total number of boundaries should be equal to twice the number of neurons.

**Strong Neuron Activation Coverage (SNAC(\(k\)))** [17]. SNAC(\(k\)) can be regarded as a special case of NBC(\(k\)) as it only takes upper boundary into consideration. Thus, it is defined as the ratio of the number of covered upper boundaries and the total number of upper boundaries, in which the latter is actually equal to the number of neurons in a DNN.

**Top-\(k\) Neuron Coverage (TKNC(\(k\)))** [17]. TKNC(\(k\)) measures how many neurons have once been the most active \(k\) neurons on each layer. It is defined as the ratio of the total number of top-\(k\) neurons on each layer and the total number of neurons in a DNN. We say a neuron is covered by a test if and only if when the DNN is run against the test, the output of the neuron is larger than or equal to the \(k\)th highest value in the layer of the neuron.

It is noteworthy that, according to this definition, this metric only can be used to compare two test sets with more than one test. For each single test, it always covers \(k\) neurons in each layer of a DNN. Thus, the coverage rates of TKNC(\(k\)) are always the same for two single tests, and CTM does work using this coverage metric.

3 COVERAGE-BASED TEST PRIORITIZATION
In conventional software testing, this is actually a classic problem known as test prioritization (a.k.a. test case prioritization), which is defined by Rothermel et al. [26] as following:

**Test Prioritization.** Given a test set \(T\), the set \(PT\) of the permutations of \(T\), and a function \(f\) from \(PT\) to the real numbers, the test prioritization problem is to find \(T' \in PT\) such that

\[
\forall T'' \in PT \setminus \{T'\} : f(T') \geq f(T'').
\]

Here, \(f(T' \in PT)\) yields an award value for a permutation.

In the past decades, many test prioritization techniques have been proposed for conventional software. Most of these techniques are based on various code coverage information and follow the basic assumption that early maximization of coverage would lead to early detection of faults [7]. Two main coverage-based techniques are known as coverage-total and coverage-additional test prioritization [37]. A coverage-total method prioritizes tests based on their individual total coverage. That is, we prefer a test to the other one if it covers more program elements. For the example in Table 1, a coverage-total method will produce a permutation, \(A, B, C, D\), in which \(A\) is the first one because it covers the most number of program statements. A coverage-additional method differs from the coverage-total method in that, it prefers a test if it can cover more program elements that have not been covered. For the example in Table 1, a coverage-additional method will produce a permutation, \(A, D, C, B\), in which \(D\) is selected before \(C\) and \(B\) because it covers the most statements that have not been covered.

**Table 1:** An example to illustrate coverage-based test prioritization. ‘X’ means a statement is covered by a test.

| Test | Program Statement |
|------|-------------------|
| A    | X X X X X X X X |
| B    | X X X X X X     |
| C    | X X X X X       |
| D    | X X X X         |

In the area of conventional software testing, most of the proposed test prioritization methods are coverage-based, in which
Coverage-total and coverage-additional are the most widely-used methods [37].

**Coverage-Total Method (CTM).** A CTM is an implementation of the “next best” strategy. It always selects the test with the highest coverage rate, followed by the test with the second-highest coverage rate, and so on. For tests with the same coverage rate, the method will prioritize them randomly. For the example in Table 1, both A, B, C, D and A, B, D, C are valid results of CTM.

CTM is attractive because it is relatively efficient and easy to implement. Given a set consisting of n tests with their coverage rates, CTM only needs to sort these tests according to their coverage rates. Typically, using a quick sort algorithm, it only takes \( O(n \log n) \) time [5].

**Coverage-Additional Method (CAM).** CAM differs from CTM in that it selects the next test according to the feedback from previous selections. It iteratively selects a test that can cover more uncovered code structures. In this manner, we can expect that we can achieve the maximum coverage rate of a test set as soon as possible. After the maximum coverage rate is achieved, we can use CTM to prioritize the remaining unprioritized tests. For the example in Table 1, A, D, C, B is the only valid result of CAM.

Given a program with \( m \) elements to cover and a set of \( n \) tests, every time we select a test, it will take \( O(mn) \) time to readjust the coverage information of the remaining tests. This process will be performed \( O(n) \) times. Thus, the total time cost is \( O(mn^2) \). According to the time complexity, it is easy to find that CAM is less scalable compared to CTM, especially when \( n \) and \( m \) are very large.

### 4 APPROACH

To reduce the cost of labeling tests in the testing of DNN-based systems, we propose DeepGini, a prioritization technique to assist tester in identifying the misclassification tests in a short time. Rather than employing the neuron-coverage as the metric to guide the prioritization, we construct DeepGini based on a statistical view of DNN as discussed in Section 4.1. In this section, we detail the design of DeepGini.

#### 4.1 A Statistical View of DNN

DNNs are specially good at classifying high-dimensional objects. If we regard each output class of a DNN as a kind of feature of the input object, the computation (or classification) process of a DNN actually maps the original high-dimensional data to only a few kinds of features. As an example, suppose the input of a DNN is a 28x28 image with three channels (i.e., RGB channels). Then the original dimension of the image is \( 2^{28 \times 28} \). Figure 1, the DNN maps the high-dimension object to a multi-set (or bag) \( B \) of features, in which 94\% are features of monkey, 1\% are features of tiger, 3\% are features of dog, and 2\% are features of cat. Since most elements in \( B \) are features of monkey, we classify the input object into the monkey class.

Generally, if the feature bag \( B \) has the highest purity, i.e., contains only one kind of features (e.g., 100\% elements in \( B \) are features of monkey), then there will be no other features confusing our classification and it is more likely that a test input is correctly classified. Intuitively, if a bag has higher purity, the results of two random samplings in the bag have higher probability to be the same. In contrast, if a bag has lower purity, the results of two random samplings in the bag are more likely to be different. Assuming the proportion of various features in \( B \) is a probability vector \( \langle p_1, p_2, \ldots, p_N \rangle \), using sampling with replacement, \( N \) can compute the probability that two random samplings have different results as \( 1 - \sum_{i=1}^{N} p_i^2 \). The lower the probability, the higher the purity and, thus, the more likely a test input of a DNN is correctly classified.

On the statistical view, we can observe that the problem of measuring the likelihood of misclassification actually has been transformed to the problem of measuring the purity of a bag. In fact, such a transformation follows the very spirit of the measurement of Gini impurity [21], which inspires us to propose DeepGini for measuring the likelihood of misclassification.

#### 4.2 DeepGini: Prioritizing Tests of a DNN

Formally, the metric we use to measure the likelihood of misclassification is defined as below.

**Definition 4.1.** Given a test \( t \) and a DNN that outputs \( \langle p_{t,1}, p_{t,2}, \ldots, p_{t,N} \rangle (\sum_{i=1}^{N} p_{t,i} = 1) \), we define \( \xi(t) \) to measure the likelihood of \( t \) being misclassified:

\[
\xi(t) = 1 - \sum_{i=1}^{N} p_{t,i}^2
\]

In the definition, \( p_{t,i} \) is the probability that the test \( t \) belongs to the class \( i \). Figure 2 illustrates the distribution of \( \xi \) when the DNN performs a binary classification. The distribution illustrates that when DNN outputs the same probability for the two classes, \( \xi \) has the maximum value, indicating that we have high probability to incorrectly classify the input test. This result follows our intuition that a test is likely to be misclassified if the DNN outputs similar probabilities for each class, and the rationality of the result has been explained in the previous subsection. The following theorem demonstrates that even though a DNN classifies input tests into more than two classes, \( \xi \) has a similar distribution as in Figure 2.

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3 A multi-set or a bag is a special kind of set that allows duplicate elements.
Theorem 4.2. \( \xi(t) \) has the unique maximum if and only if \( \forall i \leq j \leq N : p_{t,i} = p_{t,j} \).

Proof. According to Lagrangian multiplier method [23], let

\[
L(p_{t,i}, \lambda) = \xi(t) + \lambda \times (\sum_{i=1}^{N} p_{t,i} - 1)
\]

\( \forall p_{t,i} \), let

\[
\frac{\partial L}{\partial p_{t,1}} = -2p_{t,1} + \lambda = 0
\]

\[
\frac{\partial L}{\partial p_{t,2}} = -2p_{t,2} + \lambda = 0
\]

\[\vdots\]

\[
\frac{\partial L}{\partial p_{t,N}} = -2p_{t,N} + \lambda = 0
\]

If we calculate the difference of any two above equations (e.g. the \( i \)th and \( j \)th equation), we will have

\[2p_{t,1} - 2p_{t,j} = 0 \Rightarrow p_{t,1} = p_{t,j}\]

Hence, when \( p_{t,1} = p_{t,2} = \cdots = p_{t,N} = 1/N \), \( \xi(t) \) has the unique extremum.

At the point \((p_{t,1}, p_{t,2}, \cdots, p_{t,N})\), the Hessian matrix [1] of \( \xi \) is

\[
\begin{pmatrix}
-2 & 0 & \cdots & 0 \\
0 & -2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & -2
\end{pmatrix}
\]

which is a negative definite matrix. This implies that the unique extremum must be the unique maximum [1].

We notice that many other metrics such as information entropy [27] also have the above property and is almost equivalent to \( \xi \) [22]. The difference is that it may require a non-statistical view, e.g., the perspective of information theory, to explain the rationality.

In addition, we believe that the simplest is the best: the complexity of computing quadratic sum is much easier than that of computing entropy-like metrics because they require logarithmic computation.

According to the above discussion, \( \xi(t_1) > \xi(t_2) \) implies that \( t_1 \) is more likely to be misclassified. Hence, to prioritize \( n \) tests in a set, we need to run the tests to collect the outputs, and then sort these tests \( t_i \) according to the value of \( \xi \).

We argue that the time cost of running the tests is negligible. First, the time cost to run a DNN is not time-consuming like training the DNN. Compared to the expensive cost of manually labeling all tests in a messy order, the time cost is completely negligible. Second, this issue is shared with all neuron-coverage-based test prioritization methods as they also need to run tests to obtain the coverage rates.

Example 4.3. Assume that we have four tests \( A, B, C, \) and \( D \) as well as a DNN tries to classify them into three classes. Table 2 shows their output vectors and the values of \( \xi \).

According to the values of \( \xi \), we can prioritize the tests as \( D, A, C, \) and \( B, D \) has the highest probability to be misclassified because the DNN outputs the most similar probabilities for each of the three classes.

In comparison, for \( B \) and \( C \), the DNN is more confident about their classes as \( B \) has the probability of 0.8 to be classified into the third class and \( C \) has the probability of 0.6 to be classified into the first class.

Typically, in our prioritization method, we can simply use a quick sort algorithm to sort tests. This algorithm takes \( O(n \log n) \) time complexity. Compared to CTM and CAM, our approach has following merits:

- The time complexity of our approach is the same with CTM and is much lower than CAM (\( O(mn^2) \)). Thus, our approach is as scalable as CTM and much more scalable than CAM.
- Different from CTM and CAM, we only need to record output vectors while CTM and CAM require us to profile the whole DNN to record coverage information. Thus, our approach has less interference with the DNN.

5 EXPERIMENT DESIGN

In this section, we introduce the experiment settings. As we introduced in the Section 4, DeepGini is designed for facilitating the tester of DNN-based systems to identify the misclassified tests in earlier stage. Based on this goal, in this experiment, we first measure the effectiveness of DeepGini. Furthermore, when testing the DNN-based systems, testers are often required to finish the testing tasks in limited time resource. Under this situation, time cost becomes critical for the testing work. Thus, we also measure the efficiency in our experiment.

We develop the following two research questions:

- **RQ1 (Effectiveness):** Can our prioritization method find a better permutation of tests than neuron-coverage-based methods?
- **RQ2 (Efficiency):** Is our prioritization method more efficient or scalable than neuron-coverage-based methods?

To answer these questions, we implement our approach as well as various neuron-coverage-based test prioritization methods upon Keras 2.1.3 with TensorFlow 1.5.0.6-7. All of our implementation can be access via: https://github.com/deepgini/deepgini

\[\text{https://farosf.github.io/keras-docs/2.1.3/}\]

\[\text{https://github.com/tensorflow/tensorflow/releases}\]

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Table 2: An example to illustrate how to use \( \xi \) to prioritize tests.

| Test | Output of DNN | \( \xi \) |
|------|---------------|----------|
| A    | (0.3, 0.5, 0.2) | 0.62     |
| B    | (0.1, 0.1, 0.8) | 0.34     |
| C    | (0.6, 0.3, 0.1) | 0.54     |
| D    | (0.4, 0.4, 0.2) | 0.64     |
5.1 Datasets and DNN Models

As shown in Table 3, for evaluation, we select four popular publicly-available datasets, i.e., MNIST, CIFAR-10, Fashion-MNIST, and SVHN.

The MNIST dataset is for handwritten digits recognition, containing 70,000 input data in total, of which 60,000 are training data and 10,000 are test data.

The CIFAR-10 dataset consists of 60,000 32x32 colour images in 10 classes, with 6,000 images per class. There are 50,000 training images and 10,000 test images.

Fashion-MNIST is a dataset of Zalando’s article images consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 gray-scale image, associated with a label from 10 classes.

SVHN is a real-world image dataset that can be seen as similar in flavor to MNIST (e.g., the images are of small cropped digits), but incorporates an order of magnitude more labeled data (over 600,000 digit images).

On MNIST and CIFAR-10, we use the pre-trained LeNet-5 and ResNet-20 as the DNN models, respectively. For the other two datasets, since we do not find any available pre-trained DNN models, we train the DNN models by ourselves using LeNet-5.

5.2 Adversarial Test Input Generation.

In addition to prioritizing original tests in the datasets, we also conduct an experiment to prioritize adversarial tests. As in the previous studies [17], we use four state-of-the-art methods to generate adversarial tests, including FGSM [8], BIM [15], JSMA [19], and CW [4]. These adversarial techniques generate tests through different minor perturbations on a given test input. Figure 3 illustrates some adversarial tests generated by these methods. Table 3 shows the total number of adversarial tests generated by these methods.

5.3 Baseline: Neuron-Coverage-Based Methods

We compare our approach to neuron-coverage-based methods that use five different coverage criteria as introduced in Section 2. Since these coverage criteria contain configurable parameters, as shown in Table 4, we use the various parameters as suggested by their original authors.

Each comparison experiment is conducted in four modes with regard to two aspects: (1) using CTM or CAM to prioritize tests; and (2) prioritizing tests in the original datasets or prioritizing tests that combine the original tests and adversarial tests.

5.4 Metrics: APFD and Time Cost

In each comparison experiment, we record the time cost of prioritization, so that we can compare the efficiency of these methods. Also, we compute the values of Average Percentage of Fault-Detection (APFD) metric [37] to compare the effectiveness of these methods. Higher APFD values denote faster misclassification-detection rates. When plotting the percentage of detected misclassified tests against the number of prioritized tests, APFD can be calculated as the area below the plotted line. It is also noteworthy that although an APFD value ranges from 0 to 1, an APFD value not close to 1 does not mean that the prioritization is ineffective. This is mainly because the theoretically maximal APFD value is usually much less than 1 [37]. Formally, for a permutation of n tests in which there are k tests will be misclassified, let $o_i$ be the order of the first test that reveals the $i$th misclassified test. The APFD value for this permutation can be calculated as following:

$$\text{APFD} = 1 - \frac{\sum_{i=1}^{k} o_i}{kn} + \frac{1}{2n}$$

All the experiments were performed on a computer with two 20 core processors “Intel(R) Xeon(R) CPU E5-2698 v4 @ 2.20GHz” and 512GB physical memory running CentOS Linux release 7.4.1708. To measure the time cost of experimental methods, we record the execution time.

6 RESULT ANALYSIS & DISCUSSION

All the evaluation results are listed in Table 5 and are available online: https://github.com/deepgini/deepgini. In Columns 4 and 7, we show the minimal number of tests that can achieve the maximum coverage rate of a test set. We also show the time cost of prioritization as well as the APFD values in Columns 5, 6, 8, and 9. In the following subsections, we try to visualize these results and analyze the reasons behind them. We summarize our findings in Section 6.4 and discuss the threats to validity in Section 6.5.

6.1 Comparing with NAC($k$)-, NBC($k$)-, and SNAC($k$)-Based Methods

According to Table 5, for all the four datasets, less than 0.5% tests are sufficient for us to achieve the maximum coverage rate of the three coverage criteria: NAC($k$), NBC($k$)-, and SNAC($k$), regardless of the value of $k$. For example, in the 10,000 original tests of MNIST, 20 tests are enough to achieve the maximum coverage rate, 88%, of NAC(0.75). As discussed in Section 3, the strategy of CAM will...
Table 3: Datasets and DNN models.

| Dataset       | Description          | DNN Model | #Neurons | #Layers | # Original Tests | # Adversarial Tests |
|---------------|----------------------|-----------|----------|---------|-----------------|--------------------|
| MNIST         | Digits 0–9           | LeNet-5   | 268      | 9       | 10,000          | 39,705             |
| CIFAR-10      | Images with 10 classes| ResNet-20 | 698      | 20      | 10,000          | 40,000             |
| Fashion-MNIST | Zalando’s article images| LeNet-5  | 268      | 9       | 10,000          | 39,924             |
| SVHN          | Street view house numbers| LeNet-5 | 268      | 9       | 26,032          | 104,037            |

Figure 4: Test prioritization for MNIST. X-Axis: prioritized original tests (Up), or both original and adversarial tests (Below); Y-Axis: the number of detected misclassified tests.

Table 4: Configuration parameters for the coverage criteria.

| Criteria       | Configuration Parameter k |
|----------------|---------------------------|
| NAC(k)         | 0, 0.75, N/A              |
| KMNC(k)        | 1,000, 10,000, N/A        |
| NBC(k)         | 0, 0.5, 1                 |
| SNAC(k)        | 0, 0.5, 1                 |
| TKNC(k)        | 1, 2, 3                   |

Remark 1. CAM will quickly degenerate into CTM for NAC(k)−, NBC(k)−, and SNAC(k) because only a small number of tests can achieve the maximum coverage rate.

Remark 2. CTM is not effective when NAC(k)−, NBC(k)−, and SNAC(k) are used.

6.2 Comparing with KMNC(k)-Based Methods
As discussed in Section 2.2, CTM does not work if we use KMNC(k) to prioritize tests, because almost all single tests have the same coverage rate of KMNC(k), regardless of the value of k. Thus, we only compare KMNC(k)-based CAM with our prioritization method.

Effectiveness. The effectiveness of KMNC(k)-based CAM method is not appealing. Using MNIST as an example, Figure 4(b) shows that the curve of our method goes up far more quickly than KMNC(k)-based method. The APFD values in Table 5 also demonstrate that our method is much better due to higher APFD values.

Efficiency. When prioritizing tests using KMNC(k)-based CAM method, we also observe efficiency issues. That is, since the time complexity of the method is very high, we usually cannot finish prioritizing tests in an acceptable time budget. For example, for CIFAR-10, we have $n = 10,000$ original tests or $n = 50,000$ original and adversarial tests, as well as $m = 698k$ ($k = 1, 000$ or 10,000) degenerate into CTM after achieving the maximum coverage rate. Thus, the effectiveness and the efficiency of CAM are almost the same as CTM for these datasets.

Effectiveness. Using MNIST as an example, Figure 4(a) plots the number of detected misclassified tests against the prioritized tests. We have two observations from this figure. First, our prioritization method can find more misclassified tests much faster than neuron-coverage-based methods. Second, as illustrated by the dotted line in Figure 4(a), neuron-coverage-based prioritization methods, sometimes, are even worse than the random prioritization.

Efficiency. Since CAM degenerates into CTM as explained above and both the CTM method and our method use quick-sort to prioritize tests, the differences between their time cost are not significant.
| Data Sets | Metrics | Param. | Original Tests | Original + Adv. Tests |
|-----------|---------|--------|----------------|----------------------|
|           |         |        | Max. Coverage (%) | CTM (sec/AFPD) | CAM (sec/AFPD) | Max. Coverage (%) | CTM (sec/AFPD) | CAM (sec/AFPD) |
| NAC(k)    | 0       | 100/1  | 140/64 | 15/50 | 100/1  | 67/46 | 69/50  |
|           | 0.75    | 88/20  | 150/43 | 18/38 | 90/24  | 68/47 | 76/49  |
| KMNC(k)   | 1000    | 63/8816| N/A    | 4hrs/0.59 | 72/1828 | N/A    | 11hrs/0.45 |
|           | 10000   |        |        |        |        |        |        |
|           | T.O.    |        |        |        |        |        |        |
| NAC(k)    | 0       | 8/38   | 41/64  | 50/50 | 15/56  | 128/47 | 136/50 |
|           | 0.5     | 1/5    | 39/64  | 44/53 | 3/11   | 103/47 | 105/50 |
|           | 1       | 0.4/3  | 380/64 | 46/48 | 2/7    | 105/47 | 108/50 |
| SNAC(k)   | 0       | 14/35  | 41/64  | 52/46 | 22/48  | 120/47 | 124/50 |
|           | 0.5     | 2/5    | 35/64  | 48/54 | 7/11   | 106/47 | 108/50 |
|           | 1       | 0.8/3  | 340/64 | 49/54 | 4/7    | 105/47 | 108/50 |
| TKNC(k)   | 1       | 66/85  | N/A    | 20/54 | 74/95  | 99/50  |        |
|           | 2       | 73/63  | N/A    | 18/51 | 79/71  | N/A    | 82/50  |
|           | 3       | 76/55  | N/A    | 18/48 | 81/53  | N/A    | 82/50  |
| DeepGini  | N/A     | N/A    | 2/0.98 | N/A   | N/A    | 5/0.60 |        |
| CIFAR-10  | NAC(k)  | 0      | 100/1  | 300/51 | 328/51 | 100/1  | 665/47 | 1491/50 |
|           | 0.75    | 47/50  | 350/42 | 396/50 | 51/48  | 792/49 | 1674/50 |
| KMNC(k)   | 1000    | N/A    | N/A    | N/A   | N/A    | N/A    |        |
|           | 10000   |        |        |        |        |        |        |
|           | T.O.    |        |        |        |        |        |        |
|           | T.O.    |        |        |        |        |        |        |
| NAC(k)    | 0       | 10/94  | 1520/50 | 190/50 | 25/132 | 3192/47 | 3838/50 |
|           | 0.5     | 3/27   | 1357/51 | 169/51 | 14/42  | 2855/47 | 3377/50 |
|           | 1       | 2/16   | 1355/51 | 176/51 | 12/26  | 2840/47 | 3568/50 |
| SNAC(k)   | 0       | 14/63  | 1776/51 | 253/50 | 37/79  | 3505/47 | 4597/50 |
|           | 0.5     | 6/27   | 1676/51 | 229/50 | 29/42  | 3495/47 | 4347/50 |
|           | 1       | 3/16   | 1721/51 | 242/50 | 24/26  | 3521/47 | 4325/50 |
| TKNC(k)   | 1       | 59/136 | N/A    | 300/50 | 62/135 | 1008/50 |        |
|           | 2       | 69/9  | N/A    | 348/50 | 73/116 | N/A    | 1061/50 |
|           | 3       | 76/106 | N/A    | 381/50 | 78/108 | N/A    | 1106/50 |
| DeepGini  | N/A     | N/A    | 34/0.83 | N/A   | N/A    | 61/0.58 |        |
| Fashion-MNIST | NAC(k) | 0       | 7/25   | 44/51  | 49/49  | 15/52  | 120/47 | 137/50 |
|           | 0.5     | 3/10   | 42/51  | 46/51  | 8/31   | 110/47 | 120/50 |
|           | 1       | 0.4/3  | 40/51  | 46/49  | 4/17   | 106/47 | 115/50 |
| SNAC(k)   | 0       | 12/24  | 49/51  | 52/50  | 26/49  | 110/47 | 125/50 |
|           | 0.5     | 5/10   | 47/51  | 49/51  | 16/31  | 103/47 | 118/50 |
|           | 1       | 0.8/3  | 48/51  | 50/50  | 7/17   | 100/47 | 113/50 |
| TKNC(k)   | 1       | 76/100 | N/A    | 24/52  | 80/104 | N/A    | 115/50 |
|           | 2       | 82/72  | N/A    | 21/53  | 85/73  | N/A    | 91/50  |
|           | 3       | 85/63  | N/A    | 20/49  | 88/61  | N/A    | 86/50  |
| DeepGini  | N/A     | N/A    | 2/0.92 | N/A  | N/A    | 5/0.58 |        |
| SVHN      | NAC(k)  | 0       | 100/1  | 53/50  | 55/50  | 100/1  | 215/47 | 240/50 |
|           | 0.75    | 92/16  | 55/39  | 58/50  | 92/16  | 220/49 | 257/50 |
| KMNC(k)   | 1000    | 49/12169| N/A      | 6hrs/0.57 | N/A | T.O. |        |
|           | 10000   |        |        |        |        |        |        |
|           | T.O.    |        |        |        |        |        |        |
|           | T.O.    |        |        |        |        |        |        |
| NBC(k)    | 0       | 17/58  | 120/50 | 128/51 | 39/86  | 413/47 | 453/50 |
|           | 0.5     | 13/50  | 110/50 | 118/50 | 36/83  | 410/47 | 441/50 |
|           | 1       | 9/38   | 105/50 | 115/49 | 34/82  | 400/47 | 436/50 |
| SNAC(k)   | 0       | 34/58  | 111/50 | 122/50 | 77/86  | 322/47 | 389/50 |
|           | 0.5     | 26/50  | 105/50 | 116/51 | 72/83  | 320/47 | 380/50 |
|           | 1       | 19/38  | 106/50 | 116/50 | 68/82  | 321/47 | 384/50 |
| TKNC(k)   | 1       | 87/117 | N/A    | 71/50  | 89/116 | N/A    | 316/50 |
|           | 2       | 90/76  | N/A    | 64/49  | 90/69  | N/A    | 243/50 |
|           | 3       | 90/57  | N/A    | 52/49  | 91/53  | N/A    | 220/50 |
| DeepGini  | N/A     | N/A    | 10/0.84 | N/A   | N/A    | 21/0.58 |        |

N/A: Not Applicable; T.O. Time Out (> 12 hours)
neuron-output sections to cover. Due to the high time complexity $O(mn^2)$, we never succeed prioritizing tests using the method in 12 hours.

Remark 3. CAM is not scalable due to its high complexity when KMNC($k$) is used.

Remark 4. CTM does not work when KMNC($k$) is used because almost all single tests have the same coverage rate.

6.3 Comparing with TKNC($k$)-Based Methods
As discussed in Section 2.2, every single test has the same coverage rate of TKNC($k$), regardless of the value of $k$. Thus, CTM does not work if we use TKNC($k$) to prioritize tests. Unfortunately, CAM also does not work using this coverage metric. The main reason is that only about 1% tests are enough to achieve the maximal coverage rate. And after prioritizing the 1% tests, CAM is degenerate into CTM, which does not work as explained above. Thus, we only can randomly prioritize the remaining tests.

Effectiveness. Using MNIST as an example, Figure 4(c) plots the prioritization results, in which the curve of our method goes up far more quickly than TKNC($k$)-based method. Thus, our method is much better in effectiveness.

Efficiency. Table 5 shows that such a prioritization method takes similar time cost with our method.

Remark 5. CAM will quickly degenerate into CTM for TKNC($k$) because only a small number of tests can achieve the maximum coverage rate.

Remark 6. CTM does not work when TKNC($k$) is used because all single tests have the same coverage rate.

6.4 Summary of Our Findings
Based on the evaluation results and our analysis, we summarize our findings as following:

1. With regard to existing neuron coverage criteria, CAM is not effective to prioritize tests for DNNs, because of two reasons. First, except for KMNC($k$), we can easily achieve the maximal coverage rate using only a few tests. After prioritizing these tests, the strategy of CAM becomes meaningless. Second, as discussed before, the time complexity of CAM is $O(mn^2)$. When the number of tests $n$ is very large, such as in the case of KMNC($k$), it is difficult to prioritize tests in an acceptable time cost.

2. With regard to existing neuron coverage criteria, CTM is also not effective to prioritize tests for DNNs. According to the evaluation results, the prioritization results of CTM sometimes are even worse than a random prioritization.

3. Our metric is very effective for test prioritization. In many cases, its APFD values are very close to the theoretically maximal value. In addition, it is very efficient and does not require to record the intermediate results of a DNN.

6.5 Threats to Validity
The threats to validity come from three aspects. First, the datasets and DNN models we used in our evaluation could be threats. We try to counter the threats by using the commonly-used datasets and existing pre-trained DNN models. These datasets are widely used in different areas of computer science and engineering, such as machine learning and computer vision.

Second, the configurable parameters used in each coverage criteria could be a threat. We attempt to counter this threat by using different parameters as in the literature where they are proposed. For example, for the coverage criterion KMNC($k$), we studied $k = 1,000$ and $k = 10,000$ as in the original literature [17].

Third, the methods we used for adversarial test generation could be a threat. In our evaluation, we used four state-of-the-art techniques that can generate adversarial tests. When generating adversarial tests, we use their default settings. Even though, since the four methods are only the tip of the iceberg and there are many other methods, some of our results might not generalize to the tests generated by them.

7 RELATED WORK
We discuss the related work in two groups: (1) test prioritization methods for conventional software and (2) testing techniques for deep learning systems.

7.1 Test Prioritization Techniques
Test prioritization seeks to find the ideal ordering of tests, so that software testers or developers can obtain maximal benefit in a limited time budget. The idea was first mentioned by Wong et al. [35] and then the technique was proposed by Harrold and Rothermel [9, 24] in a more general context. We observe that such an idea from the area of software engineering can significantly reduce the effort of labeling for deep learning systems. This is mainly because a deep learning system usually has a large number of unlabeled tests but software developers only have limited time for labeling.

Coverage-based test prioritization, such as the CAM and CTM studied in this paper, is one of the most commonly studied prioritization techniques. In conventional software engineering, we can obtain a new prioritization method when a different coverage criterion is applied. Rothermel et al. [25, 26] reported empirical studies of several coverage-based approaches, driven by branch coverage, statement coverage, and so-called FEP, a coverage criterion inspired by mutation testing [3]. In addition, Jones and Harrold [11] reported that MC/DC, a stricter form of branch coverage, is also applicable to coverage-based test prioritization. Different from the above techniques, we focus on testing and debugging for deep learning systems. Thus, we studied test prioritization based on coverage criteria that specially proposed for DNNs, including NAC [20], KMNC, NBC, SNAC, and TKNC [17]. Our study demonstrated that, using these coverage criteria, coverage-based test prioritization is not effective and efficient. Sometimes, its effectiveness is even worse than random prioritization. Instead, our approach uses a simple
metric that does not require to profile the DNNs but is effective and also efficient.

We notice that, in software engineering, there are also many prioritization techniques based on metrics other than coverage criteria, including distribution-based approach [16], human-based approach [33, 38], history-based approach [28], model-based approach [12–14], and so on. These techniques are usually specially-designed for conventional software systems instead of deep learning systems. Making them applicable to deep learning systems may require non-trivial efforts of re-design. We leave them as our future work.

8 CONCLUSION

Based on a statistical view of DNN, we have introduced a metric called DeepGini for measuring the likelihood of misclassification. This metric can be used to prioritize tests so that we can find as many misclassified tests as possible in a short time. Experimental results demonstrate that it is more effective than neuron-coverage-based methods. In real-world scenario, tests usually do not have labels and we have to invest a lot of manpower to label them. With such a prioritization method in hand, we can achieve maximal benefit, even the labeling process is prematurely halted at some arbitrary point due to resource limits.

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