A Neural Network Based Novel Test Selector

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ABSTRACT

Machine learning (ML) has been used to accelerate the progress of functional coverage in simulation-based verification. A supervised ML algorithm, as a prevalent option in the previous work, is used to bias the test generation or filter the generated tests. However, for missing coverage events, these algorithms lack the positive examples to learn from in the training phase. Therefore, the tests generated or filtered by the algorithms cannot effectively fill the coverage holes. This is more severe when verifying large-scale design because the coverage space is larger and the functionalities are more complex. This paper presents a configurable framework of test selection based on neural networks (NN), which can achieve a similar coverage gain as random simulation with far less simulation effort under three configurations of the framework. Moreover, the performance of the framework is not limited by the number of coverage events being hit. A commercial signal processing unit is used in the experiment to demonstrate the effectiveness of the framework. Compared to the random simulation, NNBNTS can reduce up to 53.74% of simulation time to reach 99% coverage level.

KEYWORDS

Simulation-Based Verification, Functional Coverage, Novelty Detection, Deep Learning

1 INTRODUCTION

Simulation-based verification is a vital technique that is used to gain confidence in the functional correctness of digital designs. Traditionally, the quality of a generated test is measured by various coverage metrics obtained during simulation. Functional coverage records the execution status of the specified functionality. In practice, functional coverage closure requires extensive simulation. Moreover, even a test that has been very carefully crafted by experienced engineers may not improve coverage. These barriers slow down the development of digital design and become more severe because of the increasing complexity of modern digital designs.

In recent years, ML is reported to effectively automate Coverage Directed Test Generation (CDG) and accelerate the progress of functional coverage [9]. Although the effectiveness of the ML-CDG framework has been demonstrated in previous works, several knowledge gaps still exist that prevent ML models to accelerate simulation-based verification for designs of commercial complexity.

1) Gap 1: Insufficient information for learning the correlation between tests and the un-covered coverage events.

Most of the previous work adopts supervised learning algorithms that empirically learn to establish the loop between coverage analysis and test generation, i.e. the logic that would automatically alter the next tests to be run to target the coverage holes left by previous simulation rounds [9]. A shortfall affecting the training phase is that for the un-covered coverage events, there are no simulated tests for the algorithms to use as positive examples in order to learn the logic correlation between tests and the un-covered events. Therefore, the supervised algorithms cannot effectively bias test generation or filter out generated tests to target the coverage holes in the next simulation round. Rarely covered events are also affected in a similar way. To overcome this shortfall, syntax-based distance metrics have been used to identify coverage events that have been hit in syntactically close proximity to coverage holes [5]. However, syntactic proximity, e.g. based on the Hamming distance between coverage tuples, is no guarantee for semantic proximity.

2) Gap 2: The scalability of ML algorithms to accelerate the progress of functional coverage for the large-scale designs has not been sufficiently often demonstrated [9, 11].

The functionality of small designs tends to be simple and functional coverage events are highly correlated to each other, which alleviates the severity of Gap 1. For instance, if the coverage events A and B are correlated, then tests that can hit A are also very likely to hit B. Suppose A has already been covered and B is uncovered, the ML algorithms can still bias the test generator to produce the tests that can hit B by only utilizing the learned relation between tests and A.

On the other hand, Novelty Detection (ND) has also been introduced to simulation-based verification to accelerate coverage progress [2, 3, 7, 11]. This approach is based on the hypothesis that dissimilar tests hit dissimilar functional coverage events. Therefore, simulating dissimilar tests is assumed to increase coverage more effectively than random simulation of tests [7]. In [2, 7] and [3], a One-Class Support Vector Machine (OCSVM) is adopted to perform ND where the dissimilarity between tests can be measured by different kernel-induced distance metrics. Constructing such a distance metric depends on how tests are presented to the ML model, i.e., how test vectors are encoded. This restricts the portability of the OCSVM techniques across different verification projects.
Nevertheless, ND can also be implemented by an Autoencoder that does not require a user-defined distance metric to measure the novelty between tests [11]. In [11], an autoencoder is trained to reconstruct the simulated tests and future tests with high reconstruction errors are deemed novel. As an unsupervised learning technique, it has the prominent merit that the training and prediction phases are independent of the coverage space and only the test information is required. Another work demonstrates that for the NN with ReLu hidden layers, the values of hidden neurons corresponding to the novel input data reside in the corner-activation regions that have not been activated before [8]. We assume that the corner-activation region is the sparse region of the hidden neuron and distance in the test feature space (input) can be projected onto the neuron output space. Section 4 confirms this assumption and shows that the novel tests can be identified by analyzing their associated values of the hidden neurons.

Inspired by the approaches of test selection and the prominent characteristics of NN as discussed above, this paper presents a Neural Network Based Novel Test Selector (NNBNTS), of which the input is test features, but the output space can be configured to represent three definitions of novelty. NNBNTS selects the tests generated from the Constraint Random Test Generator (CRTG) to ensure novel tests are prioritized during simulation. The first configuration is to set the NNBNTS to reconstruct the input test vector and the output space is the reconstructed input space. The tests with high reconstruction errors are regarded as the novel. The second configuration is to set the NNBNTS to predict the correlation between the test feature space and the coverage space. However, instead of biasing the test generator or filtering the generated tests according to the prediction result, the novelty score calculated from the neuron outputs is assigned to each test. Unlike the two aforementioned configurations that can only conduct ND in the test feature space, the output space in the third configuration directly generates a non-linear score to indicate the novelty degree of the generated tests in the coverage space formed by the simulated tests. From the experimental results, NNBNTS can accelerate the progress of functional coverage for a particular commercial design compared to random test simulation. Although the configuration of the output space should be set before the training and deployment phase, an explicit distance metric is not required, enhancing the transferability of NNBNTS between verification projects. Moreover, the NNBNTS is easy to implement and maintain because it does not bias CSTG or modify generated tests.

The paper is structured as follows. Section 2 reviews and compares the related work to unveil the research questions yet to solve and illustrate the inspirations for this paper. Section 3 illustrates the hypothesis that simulating novel tests can enrich the cumulative coverage gain. The principle of novel test selection and the implementation of NNBNTS are also included in this section. Section 4 presents and discusses the experimental results of NNBNTS in the particular simulation-based verification environment of a commercial design.

2 PREVIOUS WORK

Previous work has embedded ML algorithms in CDG to automatically accelerate the coverage progress using fewer tests than random simulation [9]. During the training phase, ML empirically learns the correlation between the constraints used to generate the simulated tests, the simulated tests (two inputs of ML) and the corresponding coverage data (output of ML) until the satisfying prediction performance of ML is achieved. Afterwards, the trained ML can be either used to bias the test generation or filter generated tests with the aim to fill coverage holes or increase existing coverage. Retraining is necessary if the prediction quality decreases or once a coverage hole has been covered, leading to an iterative loop of training and prediction, as shown in Figure 1.

By contrast, ND, a recently introduced technique, has been shown to effectively accelerate coverage progress by arranging the simulation order of generated tests [2, 3, 7, 11]. It is assumed that tests dissimilar to those already simulated will execute functionality not yet covered, with the expectation to detect potential bugs. Existing ND approaches repeatedly select a batch of un-simulated tests for simulation, these tests are most dissimilar to the already simulated tests. The more dissimilar a test is, the higher its novelty score. In the literature, ND is mostly implemented by unsupervised learning algorithms, which means the dissimilarity is calculated in the test feature space according to a distance metric, and the training and prediction phases are de-coupled from the coverage space. Being independent of the coverage space is a distinguishing characteristic that makes the ND-based approaches not suffer from the lack of sufficiently many examples for un-hit and rarely-hit coverage events, as addressed in Gap 1.

In [2, 3, 7], ND is implemented by a One-Class Support Vector Machine (OCSVM) that requires designating a distance metric to measure the dissimilarity between tests. Nevertheless, no common distance metric can accurately capture the dissimilarity in different schemes of test encoding. In [7], every two dimensions of the feature vectors correspond to a binary bit in the test, with the unknown state X also being considered. For this test encoding scheme, both Gaussian and Dot-Product kernel functions can correctly capture the novelty in the dataset. However, if a test vector consists of continuous values instead of discrete binary bits, the Dot-Product function cannot recognize the dissimilar tests in the test feature space.
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Figure 2: Similarity in Test Feature Space and Coverage Space

Besides, in [2], each feature of the test vector is the graph-based distance from another test vector, for which the Gaussian function cannot express the dissimilarity between the test vectors.

On the contrary, an autoencoder can also be used to select novel tests. This only requires each test to be encoded as a test feature vector without designating an explicit distance metric [11]. Each feature in the test vector represents the value in each register that configures the functionality of design. The autoencoder is trained to reproduce the simulated test vectors and the novelty score is defined as the mean squared difference between the input and reproduced test vectors. A higher novelty score implies a lower number of similar tests in the training set (simulated tests) and thus the NN cannot accurately reconstruct the vector. The case study is based on the signal processing unit of the commercial design with about 6,000 white-box coverage events. The coverage events are internal signals, which are hard to hit. Therefore, the case study demonstrates the scalability of using the autoencoder to select novel tests to accelerate the progress of functional coverage for a large-scale design.

A NN is also used in [6] as a test selector to accelerate coverage progress. The NN is trained to infer the empirical correlation from the test feature space to the coverage space. Unlike other approaches that rely on the prediction result to bias the test generator, simulating tests with low-confidence prediction is reported to effectively hit the coverage holes, though the rationale is not presented. The authors of [8] associate novelty in the input space with the output value of hidden neurons. Novel data samples are regarded to have outlier values for the neuron outputs. Inspired by [8], the in this paper we assume that the density in the input space can also be projected onto the neuron output space. Furthermore, we also assume that the low-confidence outputs in [6] reside in the sparse region of the output-layer neurons for the trained logistic regression model.

3 METHODOLOGY

3.1 Hypothesis

The principle of the novel test selector is based on the hypothesis that dissimilar tests exercise dissimilar functionality of the design. This can be evidenced by more coverage events being hit by a group of dissimilar tests than a group of similar tests [7].

As it is shown in Figure 2, tests are characterized by various features, e.g. in the context of verifying the processor, a test feature can be the value in a configuration register. Each test in the feature space is represented as a test vector. The dissimilarity between test vectors is measured by a distance metric and can be correspondingly projected onto the coverage space [7]. This means the more dissimilar two test vectors are, the more coverage they can jointly achieve. Therefore, if an effective test selection scheme can identify dissimilar tests before simulation, faster progress of functional coverage can be achieved. Moreover, a mature test selection scheme from the industrial perspective should satisfy two prerequisites. First, the measure of dissimilarity between tests needs to be general enough so that algorithms can select dissimilar tests across the projects. Second, the implementation and operation schemes must be highly automatic to minimise engineering efforts.

In the ML area, comparing the difference between data samples is known as anomaly detection, which involves calculating the distance between the samples via a distance metric [1]. Novelty detection and outlier detection are implementations of anomaly detection. They mainly differ in the training data and prediction data. In outlier detection, the training data samples contain dissimilar data samples and the objective of the ML algorithm is to recognize them (outliers). In contrast, in novelty detection the training data samples are deemed to only consist of similar samples and the ML algorithm detects whether a new sample is novel compared to the training set.

3.2 Test Selection Framework

Based on our hypothesis, a framework for novel test selection for simulation-based verification is proposed in this section, as shown in Figure 3. First, un-simulated tests from CRTG are stored in the generated tests pool before test selection. The test selector was previously trained with a small number of simulated tests before being embedded into the verification environment. After the initial training, the pre-trained test selector is in the selection phase, in which the objective is to generate the novelty score for each test. Afterwards a batch of the most novel tests relative to the simulated tests is selected. The un-selected tests remain stored in the generated test tool for the following rounds of test selection. Simulating a new batch of tests dynamically changes the definition of test
novelty. To obtain the optimum performance of the test selector, retraining it with all the simulated tests after each simulation round is necessary before selecting a new batch of novel tests. The above process repeats until either the functional coverage goal is reached, or all the generated tests are simulated. The coverage information of simulated tests can also be logged in the simulated tests pool to form the training set if it is required by NNBNTS.

3.3 Construction of Test Selector

The layout of a NNBNTS is shown in Figure 4. It is based on a feedforward NN that is known as Artificial Neural Network. The test vector set is driven as the input to the NN and therefore the number of input space dimensions matches the number of features used to characterize a test vector. The neurons of adjacent layers are fully connected. The user-defined parameters for the structure of the NN include the number of neurons in each layer, the number of layers, and the activation functions, which deterministically influence the performance of the NN. However, tuning these parameters is not in the scope of this paper. Instead, configuring the prediction space and the associated novelty function is one of the main topics of this paper. Depending on the configuration of the prediction space, NNBNTS can be categorized into either Density NNBNTS, Autoencoder NNBNTS, or Coverage-Novelty NNBNTS.

For Density NNBNTS, each neuron in the prediction space is configured to output the probability of a coverage event being hit by the input test, i.e., it is a logistic regression model that estimates the correlation between the test space and coverage space. We assume that the novelty in the input space of the NN can be projected onto the output space in each subsequent hidden layer. This idea is inspired by [8], in which the distance between the input data and the training set is equal to the number of hidden neurons that are in the corner-activation areas. The corner-activation areas are ranges of values that have never occurred in the training set and are reached by new input when the NN is deployed. Therefore, it also implies the corner-activation areas are low-density regions. The novelty score for an un-simulated test in the input space is the sum of the score components calculated based on the K-nearest neighbours (KNN) of each hidden-neuron value. The search scope for KNN is within the set of the neuron values for the simulated tests. We assume that a positive correlation exists between the summed distances from the output value of a hidden neuron to its KNN and the local sparsity of that neuron. This is formally illustrated in Algorithm 1.

![Figure 4: Layout of NNBNTS](image)

Although the Density NNBNTS empirically learns the correlation between the test feature space and the coverage space, Gap 1 discussed in Section 1 is subtly circumvented by acquiring the novelty score of the input data in the output space of hidden neurons and therefore transferring the prediction task to the ND task.

On the other hand, NNBNTS can also be configured to compress input test vectors into lower dimensions and then reconstruct test vectors from the compressed dimensions. Such a configuration of a NN is known as autoencoder in the deep learning area and it is termed Autoencoder NNBNTS in this paper. The mean squared difference that expresses the reconstruction error is regarded as the novelty score as shown in Equation 1.

\[ N = \frac{1}{n} \sum_{j=1}^{n} (I_j - O_j)^2 \]

For an input test vector, \( I_j \) is the value of the \( j \)th feature, \( O_j \) is the \( j \)th reconstructed feature in the output space and \( n \) is the total number of features. In the deployment phase, the higher the reconstruction error is, the more novel the input test vector is. The

Suppose we input an un-simulated test T to the NN and N is the novelty score for T. \( O_{us} \) is the list of output values of all the hidden neurons for T. \( O_s \) is the list of output values of all the hidden neurons for the simulated tests (training set). The index of \( O_s \) is the index of hidden neurons. For instance, \( O_s[0] \) is the value set that contains outputs of hidden neuron 0 for the simulated tests. \( N_K \) is the set of values in \( O_s[i] \) which are KNN to \( O_{us}[i] \) in Euclidean space. The sum of Euclidean distances from \( O_{us}[i] \) to its KNN is the score component \( n \) obtained from hidden neuron \( i \). N is defined as the sum of \( n \) for each hidden neuron. Compared to [8], Density NNBNTS provides a more detailed approach to comparing the novelty difference between the input samples rather than just recognizing the novel inputs.

For the hidden layers in Density NNBNTS, a Leaky ReLu function is adopted as the activation function rather than the ReLu function used in [8] for two reasons. First, a ReLu neuron could never be activated after a large negative gradient flowing through the neuron, which causes the neuron to always output zero during the feedforward and backward propagation [12]. Second, the output of a ReLu neuron corresponding to all the negative inputs is zero, which causes the loss of density information from the negative territory in the input space of the neuron. By contrast, the minimum value that Leaky ReLu can represent is negative infinity.
where the test that activates few infrequently hit coverage events does not require the test information for the un-hit coverage events. Only includes the coverage information of simulated tests and thus hit coverage events can be easily mitigated. The labeling algorithm is assigned a lower N than the test that activates many frequently hit coverage events has been hit by all the simulated tests. For example, C








































































































































\begin{algorithm}
\begin{algorithmic}
\State $N \leftarrow 0$
\For{$i$ in range(0, len(C\_array))}
\If {$C_{array}[i] = 0$}
\State $n_{c_i} \leftarrow 0$
\Else
\State $n_{c_i} \leftarrow \frac{1}{\sqrt{\text{Hit\_Times[i]}}}$
\EndIf
\State $N \leftarrow N + n_{c_i}$
\EndFor
\end{algorithmic}
\caption{Generating a Training Label for a Simulated Test in Coverage-Novelty NNBNTS}
\end{algorithm}

In Algorithm 2, $C_{array}$ is the vector that records whether each coverage event has been hit by the test requiring the training label and $C_{Hit\_Times}$ is the vector that records the number of times each coverage event has been hit by all the simulated tests. For example, $C_{array}[0] = 1$ represents the coverage event 0 is hit by the test and $C_{Hit\_Times}[1] = 20$ means twenty simulated tests hit the coverage event 1. $n_{c_i}$ is 0 if the test requiring the label does not hit coverage event $i$. $N$ is the sum of $n_{c_i}$ over all the coverage events. The denominator of $n_{c_i}$ in the else branch distributes more scores to the rarely-hit coverage events of a simulated test. Thus, the situation where the test that activates few infrequently hit coverage events is assigned a lower N than the test that activates many frequently hit coverage events can be easily mitigated. The labeling algorithm only includes the coverage information of simulated tests and thus does not require the test information for the un-hit coverage events. The trained NN then is used to predict how novel an un-simulated test is with respect to the coverage space of the simulated tests.

4 EXPERIMENTAL EVALUATION

4.1 The experiment background

In this study, the design under verification is the Signal Processing Unit (SPU) of the Advanced Driver Assistance Subsystem (ADAS), which is the same one used in [11]. The SPU receives and pre-processes Radio Detection and Ranging (RADAR) data from the sensors of the vehicle based on the functional configuration which is a sequence of data being driven into the registers in the SPU. Afterwards, the pre-processed data is sent to the decision-making units of the ADAS for further actions such as braking, accelerating and steering. The SPU is a complex, safety-critical and highly configurable ADAS design.

The verification environment is simulation-based, with the test generator written in the Specman e language and the other environment components written in SystemVerilog. Each test is described by the functional configurations with 290 features that are either numerical, categorical, or binary. Domain knowledge is used to remove features that are assumed to have less effect on the target coverage model, leaving a final total of 265 features (feature engineering). Moreover, the test features are standardized with the library in Scikit-Learn [10] before being presented to NNBNTS. For the functional coverage model, there are 8409 white-box functional coverage events. The real-life project requires 6 months efforts from the verification team and simulating about 2 million constrained random tests to achieve coverage closure. For the experiment, 3076 tests are engineered, which can reproduce 100% functional coverage. In addition, 82335 tests are produced by a constrained random test generator (i.e. as random as possible within the constraints of a valid test), giving a total of 85411 tests. The coverage information of these tests is also known prior to the experiments.

NNBNTS of all the prediction spaces are constructed by using Keras [4]. For each NNBNTS in the experiment, a proportionate structure is configured. The configuration guideline is to keep the number of neurons in each hidden layer to be either twice as, half of, or the same as the previous layer. The following vectors illustrate the number of layers and the number of neurons in each layer for the NNBNTS:

Autoencoder-NNBNTS: [265, 128, 64, 128, 265]
Density-NNBNTS: [265, 512, 512, 128, 50]
Coverage-Novelty-NNBNTS: [265, 512, 265, 128, 64, 1]

Each element from the left of the vector to the right represents the number of neurons in each layer starting from the input layer. For instance, the Autoencoder-NNBNTS vector represents a NN with five layers and the input and output layers respectively have 265 and 265 neurons. The first hidden layer has 128 neurons, with another two hidden layers following it. The output space of Density-NNBNTS consists of the neurons only corresponding to the most-hit fifty coverage events. By reducing the number of neurons in the output space, the number of neurons in the hidden layers can correspondingly be reduced. Thus, the expense of calculating the novelty score for the Density NNBNTS can also be reduced. Moreover, in a real-life project, most-hit coverage events are structurally basic in terms of the syntax. This makes them easy to be recognized and embedded in the NNBNTS. However, the option of the most-hit fifty
coverage events is not the result of fine-tuning for the optimum performance of the NNBNTS. The N_K in Algorithm 1 is set to 15 and only the last three hidden layers are included in the calculation of novelty score. The rational to choose these two parameters is to reduce the training expense. They are also not the result of fine-tuning.

4.2 Experimental Results

All the NNBNTS are initialized with 500 simulated tests before the experiment. Afterwards, the 1000 most novel tests are selected to simulate in each selection round. Retraining occurs after the simulation for the selected tests and all the simulated tests and the associated coverage information (if necessary) forms of the retraining set. Table 1 shows the performance of random test simulation (RD) compared to Density (DS), Coverage-Novelty and Autoencoder (AE) NNBNTS. The first column represents the five functional coverage goals, with the top part showing the number of tests required to reach the respective coverage goal using a certain test selection technique and the bottom part showing the corresponding savings compared to random simulation. In terms of achieving coverage goals from 95% to 99.5%, NNBNTS with all the configured prediction spaces can noticeably accelerate the progress of functional coverage compared to random simulation used in traditional CRV. In this experiment, the 99% coverage goal is the point where the correlation between the test features and the remaining coverage holes becomes extremely complicated. At this point, directed tests crafted by experienced verification engineers are often more efficient in targeting the coverage holes than NNBNTS, though the latter approach is still obviously better than random simulation. We consider the best benefit is gained at 99% coverage and terminate the use of the NNBNTS-acceleration framework. To achieve our eventual 100% coverage goal, directed tests will be needed to target the coverage holes after the coverage reaching 99%

Among the results of NNBNTS, the performance of Autoencoder and Coverage-Novelty NNBNTS remains relatively stable throughout the verification. As shown in Table 1, in terms of achieving the 99.95% coverage goal, Autoencoder NNBNTS can save 24.94% of simulated tests relative to random simulation while Coverage-Novelty NNBNTS can lower the number of simulated tests by 22.59%. Although the general performance of Density NNBNTS is not as high as the other two NNBNTS, it is still better than random simulation. The computational expense for simulating a test in a large-scale design is very high. Specifically, the average simulation time for each test is 2 hours in the experiment. Thus, even a minor saving in the number of simulated tests can significantly reduce the simulation cost.

The performance of NNBNTS depends on the correlation degree from the test features to the coverage events. For instance, for Autoencoder NNBNTS, if there are many test features irrelevant to the coverage space, a test with high reconstruction errors is not necessarily novel in the coverage space. On the other hand, for supervised NN, the input features irrelevant to the output space can be filtered out during the training phase by assigning lower weights to the effects of the features on the associate neurons. However, the manual effort of engineering features for Density and Coverage-Novelty NNBNTS can still not be entirely alleviated, though the output spaces of them are related to the coverage space. First, the performance of such a method to filter out irrelevant features is limited. Second, a test feature irrelevant to the already-hit coverage events may be essential to hit existing coverage holes. Therefore, engineering test features is an indispensable requirement to deploy NNBNTS in the verification environment of commercial designs with a large coverage space. Nevertheless, this is not to say engineering features undermines the feasibility and the performance of NNBNTS. In our experiment, the expense brought by the feature engineering is still far less than the saving of simulation time gained from NNBNTS.

A more detailed comparison between the performance of the test selection techniques is shown in Figure 5, which depicts the cumulative coverage along with the progression of test simulation. NNBNTS can select more efficient tests during the verification process and thus continuously achieve similar coverage with far lower simulation effort. This also proves that the reduction in the number of simulated tests required to achieve the five coverage goals in Table 1 is not coincidental.

| Coverage Goals | RD  | DS  | CN  | AE  |
|----------------|-----|-----|-----|-----|
| 95%            | 17888 | 6262 | 5242 | 4867 |
| 97%            | 25504 | 12703 | 8579 | 9153 |
| 99%            | 48641 | 36246 | 22503 | 27599 |
| 99.5%          | 56590 | 49176 | 32969 | 38304 |
| 99.95%         | 82665 | 75318 | 63991 | 62050 |

Savings (vs. Random)   | DS  | CN  | AE  |
|-----------------------|-----|-----|-----|
| 95%                   | 64.99% | 70.70% | 72.80% |
| 97%                   | 50.19% | 66.36% | 64.11% |
| 99%                   | 25.48% | 53.74% | 43.26% |
| 99.5%                 | 13.10% | 41.74% | 32.31% |
| 99.95%                | 8.89% | 22.59% | 24.94% |

Figure 5: Result of Using NNBNTS to improve Verification Efficiency - Line Chart

Table 1: Result of Using NNBNTS to improve Verification Efficiency
Table 2: Auxiliary Result - AE OD vs AE ND

| Coverage Goals | Random | AE OD | AE ND |
|----------------|--------|-------|-------|
| 95%            | 17888  | 4842  | 4867  |
| 97%            | 25504  | 10074 | 9153  |
| 99%            | 48641  | 28835 | 27599 |
| 99.5%          | 56590  | 40852 | 38304 |
| 99.95%         | 82665  | 66944 | 62050 |

| Savings (vs. Random) | AE OD | AE ND |
|----------------------|-------|-------|
| 95%                  | 72.93%| 72.79%|
| 97%                  | 60.50%| 64.11%|
| 99%                  | 40.72%| 43.26%|
| 99.5%                | 27.81%| 32.21%|
| 99.95%               | 19.02%| 24.94%|

A characteristic of Autoencoder NN-BNTS is that the training phase does not require coverage information. In addition, the test generation phase is before any test simulation. These two characteristics inspire the outlier-test selection scheme that uses all the generated tests to train the autoencoder and select dissimilar tests within the training set. This is different from the novel test selection, in which the objective is to iteratively select a batch of new tests being novel with respect to the training set (simulated tests). Similarly, the outlier test selection uses the reconstruction error to express the dissimilarity between tests. The higher the reconstruction error is, the more dissimilar the test is.

Table 2 shows the performance comparison between the novel test selection (AE ND) and outlier test selection (AE OD). The latter approach can achieve a similar acceleration result while the computational expense of training is only about 8.3% of the former.

However, the coverage model does not include temporal logic in the experiments. Modifying the current novel test selector to accelerate the progress of coverage related to temporal functionality is our next step.

REFERENCES

[1] V. Chandola, A. Banerjee, and V. Kumar. Anomaly detection: A survey. ACM computing surveys (CSUR), 41(3):1–58, 2009.
[2] P.-H. Chang, D. Drmanac, and L.-C. Wang. Online selection of effective functional test programs based on novelty detection. In 2010 IEEE/ACM International Conference on Computer-Aided Design (ICCAD), pages 762–769. IEEE, 2010.
[3] W. Chen, N. Sumikawa, L.-C. Wang, J. Bhadra, X. Feng, and M. S. Abadir. Novel test detection to improve simulation efficiency—a commercial experiment. In 2012 IEEE/ACM International Conference on Computer-Aided Design (ICCAD), pages 101–108. IEEE, 2012.
[4] F. Chollet et al. Keras. https://keras.io, 2015.
[5] K. Eder, P. Flach, and H.-W. Haue. Towards automating simulation-based design verification using ilp. In S. Muggleton, R. Otero, and A. Tamaddoni-Nezhad, editors, Inductive Logic Programming, pages 154–168, Berlin, Heidelberg, 2007. Springer Berlin Heidelberg.
[6] S. Gogri, J. Hu, A. Tyagi, M. Quinn, S. Ramachandran, F. Batool, and A. Jagadeesh. Machine learning-guided stimulus generation for functional verification. In Design and Verification conference 2020, virtual conference, 2020.
[7] O. Guzey, L.-C. Wang, J. Levitt, and H. Foster. Functional test selection based on unsupervised support vector analysis. In 2008 45th ACM/IEEE Design Automation Conference, pages 262–267. IEEE, 2008.
[8] D. Hond, H. Asgari, and D. Jeffery. Verifying artificial neural network classifier performance using dataset dissimilarity measures. In 2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA), pages 115–121, 2020.
[9] C. Ioannides and K. I. Eder. Coverage-directed test generation automated by machine learning—a review. ACM Transactions on Design Automation of Electronic Systems (TODAES), 17(1):1–21, 2012.
[10] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830, 2011.
[11] R. H. T. Blackmore and S. Schaal. Proceedings of the 2021 design and verification conference (virtual), 2021.
[12] J. Xu, Z. Li, B. Du, M. Zhang, and J. Liu. Reluplex made more practical: Leaky relu. In 2020 IEEE Symposium on Computers and Communications (ISCC), pages 1–7. IEEE, 2020.