Abstract—Deep neural networks have been increasingly used in software engineering and program analysis tasks. They usually take a program and make some prediction about it, e.g., bug prediction. We call these models neural programs. The reliability of neural programs can impact the reliability of the encompassing analyses.

In this paper, we describe our ongoing efforts in developing effective techniques to test neural programs. We discuss the challenges in developing such tools and our future plans. In our preliminary experiment on a recent neural model proposed in the literature, we found that the model is very brittle and simple perturbations in the input can cause the model to make a mistake in its prediction.

I. INTRODUCTION

The advances of deep neural models in software engineering and program analysis research have received significant attention in recent years. Researchers have already proposed various neural models (e.g., Tree-LSTM [11], Gemini [18], GGNN [1], Code Vectors [7], code2vec [3], code2seq [2], DYPRO [14, 16], LIGER [17], Import2Vec [12]) to solve different program analysis or software engineering tasks. Each of the neural models has been evaluated by its authors but, in practice, these neural models may susceptible to untested test inputs. Therefore, a set of testing approaches has already been proposed to trace the unexpected corner-cases. Recent neural model testing techniques include [13, 19] for models of autonomous systems, [8]–[10] for models of QA systems, and [15, 17] for models of embedding systems. However, testing neural models that work on source code has received little attention from researchers except the exploration initiated by Wang et al. [15].

Evaluating the robustness of neural models that process source code is of particular importance because their robustness would impact the correctness of the encompassing analysis that use them. In this paper, we propose a transformation-based testing framework to test the correctness of the state-of-the-art neural models running on the programming task. The transformation mainly refers to the semantic changes in programs that result in similar programs. The key insight of transformation is that the transformed programs are semantically equivalent to its original form of programs but has different syntactic representation. For example, one can replace a switch statement of a program by conditional if-else statements. The original program of the switch statement is semantically equivalent to the new program of if-else statements. A set of transformations can be applied to a program to generate more semantically equivalent programs and those new transformed programs can be evaluated on neural models to test the correctness of those neural models.

The main motivation to apply transformation is the fact that such transformations may cause the neural model to behave differently and mispredict the input. We conduct a small study to see the applicability of transformations in the testing of neural models. The preliminary results show that the transformations are very effective in finding irrelevance output in neural models. We closely perceive that the semantic-preserving transformations can change the predicted output or prediction accuracy of neural models compares to the original test programs.

II. MOTIVATING EXAMPLE

We use the Figure 1 as a motivating example to highlight the usefulness of our approach. The code snippet shown in the Figure 1 is a simple java method which demonstrates the prime functionality. The only difference between these functions is that the implementation on the left uses a for loop while the implementation on the right uses a while loop instead.

We instrument the prediction of code2vec model [5] with these two equivalent functions. The code2vec takes a program and predicts the content of the program. The results of online demo [5] reveal that code2vec model successfully predicts the left-program as “isPrime” method, but could not predict the right-program as “isPrime” method. The model mistakenly predicts the right-program as a “skip” method, even the “isPrime” is not included in the top-5 predictions made by the code2vec model.

III. PROPOSED METHODOLOGY

In this section, we describe our efforts for testing neural programs. Currently, we are investigating semantic-preserving transformations that can potentially mislead a neural model of programs.
for the similarity of prediction.

**Challenges ahead** There are five main challenges that we aim to address in this project: (1) what type of transformations should perform, (2) how to preserve the semantic equivalence during transformations, (3) where to apply those transformations, (4) how to control the transformation strategy, and (5) how to evaluate the transformed programs.

**IV. OUR PLAN**

Thus far, we have applied five types of transformations. Those transformations are only capable to make basic changes in the syntactic representation of programs. However, our target is to devise more systematic transformations. We are investigating techniques and heuristics to suggest places in programs to transform, and the type of transformations that are more likely to cause the neural model to mispredict.

Moreover, we only evaluated our transformation on code2vec model [3] where the target task is labeling the method name given a method body. We have the plan to evaluate the transformation on GGGN model [1] where the target task is labeling the correct variable name based on the understanding of its usage.

Additionally, we only experimented with a small set of examples [5]. Our further plan includes a details study with larger Java dataset [4] for code2vec model and larger C# dataset [6] for GGNN model.

**V. RELATED WORK**

Several approaches for transformation-based testing have been proposed; for example, DeepTest [13] and COSET [15].

Tian et al. [13] proposed DeepTest, a tool for automated generation of real-world test images and testing of DNN-driven autonomous cars. They introduced some potential image transformation (i.e. blurring, scaling, fog and rain effect, etc.) that mimics the real-world conditions. They applied transformation-based testing to identify the numerous corner cases which may lead to serious consequences like a collision in an autonomous car. Another study in this area is DeepRoad [19] where authors applied extreme realistic image-to-image transformation (i.e. heavy rain, hard snow, etc.) with DNN-based UNIT method.

Wang et al. [15] proposed COSET, a framework for standardizing the evaluation of neural program embeddings. They applied transformation-based testing to measure the stability of neural models and identify the root cause of a misclassification. This author also implemented and evaluated a new neural model called LIGER [17] where they embed programs with runtime information rather than learning from source code.

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