Evaluation of Generalizability of Neural Program Analyzers under Semantic-Preserving Transformations

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ABSTRACT
The abundance of publicly available source code repositories, in conjunction with the advances in neural networks, has enabled data-driven approaches to program analysis. These approaches, called neural program analyzers, use neural networks to extract patterns in the programs for tasks ranging from development productivity to program reasoning. Despite the growing popularity of neural program analyzers, the extent to which their results are generalizable is unknown.

In this paper, we perform a large-scale evaluation of the generalizability of two popular neural program analyzers using seven semantically-equivalent transformations of programs. Our results caution that in many cases the neural program analyzers fail to generalize well, sometimes to programs with negligible textual differences. The results provide the initial stepping stones for quantifying robustness in neural program analyzers.

KEYWORDS
neural models, code representation, evaluation, program transformation

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1 INTRODUCTION
Abundance of publicly available source code repositories has enabled a surge in data-driven approaches to programs analysis tasks. These approaches aim to discover common programming patterns for various downstream applications[2], e.g., prediction of data types in dynamically typed languages [14], detection of the variable naming issues [3], or repair of software defects [9]. The advent of deep neural networks has accelerated the innovation in this area and has greatly enhanced the performance of these approaches. The performance of deep neural networks in cognitive tasks such as method name prediction or variable naming has reached or exceeded the performance of other data-driven approaches. The performance of neural networks has encouraged researchers to increasingly adopt the neural networks in the program analysis giving rise to increasing use of neural program analyzers.

While the performance of the neural program analyzers continues to improve, the extent to which they can generalize to new, unseen programs is still unknown. This problem is of more importance if we want to use them in downstream safety-critical tasks, such as malware detection. This problem is particularly hard, as the interpretation of neural models that constitute the core reasoning engine of neural program analyzers remains to be challenging—especially for the complex neural networks (e.g., RNN) that are commonly used for processing source code.

Reliable application of neural program analyzers requires awareness of the limits of these analyzers. A complete understanding of the extent of usefulness of such approaches would help developers to know when to use data-driven approaches and when to resort to traditional deductive methods of program analysis. It also would help researchers to focus their efforts on devising techniques to alleviate the shortcomings of these analyzers. Lack of knowledge about the limits of the neural program analyzers may exaggerate their capability and cause careless applications of the analyzers on the domains that they are not suited for; or, spending time and efforts on developing neural program analyzers while a traditional, more understandable technique can perform equally well or better.

Recently, we have seen a growing interest in the rigorous evaluation of neural program analyzers. Wang and Christodorescu [35] compared the robustness of different program representation under compiler optimization transformations. They found that the program representations based on static code features are more sensitive to such changes than dynamic code features. Allamanis [1] evaluated the impact of code duplication in various neural program analyzers and found that code duplication in the training and test datasets inflated the performance of almost all current neural program analyzers. More recently, more preliminary studies in this field started to emerge; e.g., Rabin et al. [28] proposed the idea of testing neural program analyzers using semantic-preserving transformations, and Yefet et al. [39] followed and proposed adversarial example generation for neural program analyzers using prediction attribution [32].

Goal: In this paper, we attempt to understand the limits of generalizability of neural program analyzers by comparing their behavior under semantic-preserving transformations; that is, how the result of a neural program analyzer generalizes to a semantically-equivalent program. We should note that intent from generalizability differs from Kang et al. [19]. Kang et al., in fact, evaluate the usefulness of a neural program analyzer in downstream tasks, while we evaluate their generalizability to semantically-equivalent programs. Moreover, this work, while related to, does not address the neural robustness [33] in neural program analyzers, as robustness requires...
We use code2vec \cite{5} for exposition in this section. The code2vec \cite{5} work-in-progress, Md. Rafiqul Islam Rabin and Mohammad Amin Alipour

impersonable changes to programs. Although the impact of our transformations on the semantics of the program is imperceptible, the change on the textual structure of the program is not necessarily imperceptible. Nonetheless, this work can be considered as a stepping stone towards the robustness of neural program analyzers.

In this paper, we report the results of a study on the generalizability of two highly-cited neural program analyzers: code2vec \cite{5} and code2seq \cite{4}. In this study, we transform programs from the original dataset code2seq is trained on to generate semantically-equivalent counterparts. We employ seven semantic-preserving transformations that impact the structure of programs (i.e. abstract syntax tree) with varying degrees.

Our results suggest that the models evaluated in this study are sensitive to the transformation and in many cases, transformations of a program lead the neural program analyzers to produce a different prediction than the neural program analyzers would produce on the original program. This sensitivity remains an issue even in the case of very small changes to the programs, such as renaming variables or reordering independent statements in a basic block. The result of this study is a cautionary tale that reveals that the generalizability of neural program analyzers is still far from ideal and require more attention from the research community to devise robust models of code and canonicalized program representation.

Contributions. This paper makes the following contributions.

- We introduce the notion of generalizability in neural program analyzers.
- We perform a large-scale study to evaluate the state-of-the-art neural program analyzers.
- We discuss the practical implication of our results.

2 MOTIVATING EXAMPLE

We use code2vec \cite{5} for exposition in this section. The code2vec \cite{5} is a neural program analyzer that predicts the name of a Java method given its body. Such neural program analyzer, in addition to other developer productivity tools, can be useful in classification of code, and code similarity detection.

Figure 1 shows two semantically-identical functions that implement compareTo function. The only difference between them is in the name of one of the variables. The snippet on the left uses other, while the code on the right uses var0. The results of code2vec however on these semantically equivalent programs are drastically different. code2vec predicts the snippet on the left to be compareTo function, and the function on the right to be getCount. It seems that code2vec heavily relied on the variable name other for its correct prediction.

Lack of robustness to modest changes hampers the wider application of neural program analyzers beyond developer productivity tasks, particularly in the mission-critical problem settings where higher levels of robustness and generalizability are required e.g., malware detection. Despite the significant progresses made in novel application of neural networks for program analysis tasks, their generalizability with respect to program transformations have not been adequately explored.

3 BACKGROUND

Most neural program analyzers are essentially classifiers that take a code snippet or a whole program as an input, and make predictions about some of its characteristics; e.g., a bug prediction classifier that predicts the buggy-ness of statements in the input program.

Performance of a neural program analyzer mainly depends on three main components: quality of data, the neural network architecture and its learning parameters, and the representation of data for the neural network.

Currently, most studies use open-source projects usually in mainstream programming languages, e.g., C#, Java, C, or JavaScript. The available standard datasets for these tasks are still very young and their quality is somewhat unknown. For example, a recent study by Allamanis \cite{1} showed that virtually all available datasets suffer from code duplication that can greatly impact the performance of neural program analyzers.

Another factor in the performance of neural program analyzers is source code representation. Since neural networks can only take vectors of numbers, source code embeddings are used to produce a vector representation of source code. The representation determines which program features and how to be represented in the vector embeddings. The representations can be broadly categorized into two categories: static and dynamic. Static program representations consider only the features that can be extracted from parsing text of the programs, while dynamic representations include some features pertaining to the real execution of programs.

The third building block in building a neural program analyzer is a neural network architecture and learning parameters. There are numerous choices of network architectures each with different

public int compareTo(ApplicationAttemptId var0) {
    int compareAppIds = this.getApplicationId();
    if (compareAppIds == 0) {
        return this.getAttemptId() - var0.getAttemptId();
    } else {
        return compareAppIds;
    }
}

Prediction after transformation: getCount

Figure 1: Variable Renaming on java-small/test/hadoop/ApplicationAttemptId.java file.
We have used the following seven transformations to generate semantically-equivalent programs.

- **Variable Renaming (VN)** renames the name of a variable. The new name of the variable will be in the form of varN for a value of N such that N that has not been defined in the scope.
- **Loop Exchange (LX)** replaces for loops with while loops or vice versa.
- **Switch to If (SF)** replaces a switch statement in the program with its equivalent if statement.
- **Boolean Exchange (BX)** switches the value of a boolean variable from true to false or vice versa, and propagates this change in the program to ensure a semantic equivalence of the transformed program with the original program.
- **Permute Statement (PS)** swaps two independent statements (i.e., with no dependence) in a basic block.
- **Try-Catch Insertion (TC)** adds try-catch statements to a basic block. The catch captures the highest exception in Java, i.e. Exception. Note that although this transformation does not change the behavior of the program in the normal executions, it alters the error-handling behavior of the program.
- **Unused Statement (UN)** inserts an unused string declaration to a random basic block in the program.

Note that each transformation has a different impact on the structure of programs:

- The **Variable Renaming** transformation only changes the terminal values and does not affect the structure of AST.
- The **Loop Exchange** transformation extensively impacts the AST by removing or inserting unary-not nodes.
- The **Switch to If** also impacts the AST of the program substantially by removing and inserting nodes.
- The **Permute Statement** transformation does not change the nodes in AST, rather it only reorders two subtrees in the AST.
- The **Try-Catch Insertion** transformation modifies the structure of AST by adding additional nodes and branches to realize the try-catch block.
- The **Unused Statement** transformation adds a few nodes into the AST which increases the number of paths.

### 4 EVALUATION APPROACH

In this section, we describe the experimental setting and our evaluation approach. Figure 2 depicts an overall view of the evaluation process. Our approach relies on metamorphic relations that state the output of a neural program analyzer should not substantially differ on semantically-equivalent programs. It is similar to the notion of local fidelity of classifiers that state that the behavior of classifiers should not change substantially in the vicinity of an input [29]. The approach can broadly be divided into two main steps: (1) semantic-preserving program transformation, and (2) discrepancy identification (Oracle).

#### 4.1 Transformations

We have used the following seven transformations to generate semantically-equivalent programs.

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- **Unused Statement (UN)** inserts an unused string declaration to a random basic block in the program.

#### 4.2 Oracle

Given the original program and the transformed, we try both in the neural program analyzer and compare the results. We compare the predicted label of the analyzer in both original and transformed programs. Ideally, the neural model should behave similarly with both the original and the transformed program. A discrepancy between the predicted label on the original program and the transformed program is considered prediction change.

### 5 EXPERIMENTAL SETTING

In this section, we describe the models and datasets that we used in the evaluation.

#### 5.1 Subject Neural Program Analyzers

We have used code2vec [5] and code2seq [4] neural program analyzers for the experimentation. Their task is to predict a method’s name given the body of a method.

code2vec uses a bag of AST paths to model the source code. Each path consists of a pair of terminals in the abstract syntax tree and their corresponding path between them in the AST. The path, along with source and destination terminals are mapped into its vector embeddings which are learned jointly with other network parameters during training. The three separate vectors of each path-context are then concatenated to a single context vector using a fully connected layer which is learned during training with the network. An attention vector is also learned with the network which is used to score each path-context and aggregate multiple path-contexts to a single code vector representing the method’s body. After that, the model predicts the probability of each target method’s name given the code vector of method’s body with a softmax-normalization between the code vector and each of the embeddings of target method’s name.

code2vec uses monolithic path embeddings and only generates a single label at a time, while the code2seq model uses an encoder-decoder architecture to encode paths node-by-node and generate label as sequences at each step. The encoder represents a method’s body as a set of AST paths where each path is compressed to a fixed-length vector using a bi-directional LSTM which encodes paths node-by-node. The decoder uses attention to select relevant
paths while decoding and predicts sub-tokens of target sequence at each step when generating the method’s name.

5.2 Datasets
The datasets published along with code2vec only contains the programs in preprocessed format, but, for this study, we needed the raw Java files to make the transformations. Fortunately, the datasets accompanied by code2seq contained the java files, and code2seq and code2vec shared the same code pre-processing techniques. Therefore, we used the code2seq dataset for training neural program analyzers for the study.

There are three Java datasets: Java-Small, Java-Med, and Java-Large.

- **Java-Small**: This dataset contains 9 Java projects for training, 1 for validation and 1 for testing. Overall, it contains about 700K methods. The compressed size is about 366MB and the extracted size is about 1.9GB.
- **Java-Med**: This dataset contains 800 Java projects for training, 100 for validation and 100 for testing. Overall, it contains about 4M examples. The compressed size is about 1.8GB and the extracted size is about 9.3GB.
- **Java-Large**: This dataset contains 9000 Java projects for training, 200 for validation and 300 for testing. Overall, it contains about 16M examples. The compressed size is about 7.2GB and the extracted size is about 37GB.

5.3 Training Models per Datasets
The authors of code2vec and code2seq have made the programs for training a neural model and evaluating it public. We use their tools on three aforementioned datasets to train and create three code2vec neural program analyzers and three code2seq code2seq.

We train each model up to 100 epochs and save after each epoch. We stop in an earlier epoch if the F1 score, in that epoch, is reasonably close to the score reported in the corresponding paper. Otherwise, we continue for 100 epochs and select the model in the epoch with the highest F1 score. Table 1 summarizes the characteristics of the trained models. While the performance of our trained models for code2vec is on par with to the ones reported in the corresponding paper [4], the performance of code2vec, after 100 epochs did not reach the performance reported in [5], perhaps due to the differences in the dataset. However, the performance of our trained code2vec models is similar to the one reported in [4].

### Table 1: Characteristics of the models in neural program analyzer.

| Model    | Dataset     | Precision | Recall | F1 Score |
|----------|-------------|-----------|--------|----------|
| code2vec | JAVA-SMALL  | 28.36     | 22.37  | 25.01    |
|          | JAVA-MED    | 42.55     | 30.85  | 35.76    |
|          | JAVA-LARGE  | 45.17     | 32.28  | 37.65    |
| code2seq | JAVA-SMALL  | 46.30     | 38.81  | 42.23    |
|          | JAVA-MED    | 59.94     | 48.03  | 53.33    |
|          | JAVA-LARGE  | 64.03     | 55.02  | 59.19    |

5.4 Population of Transformed Programs
We apply the applicable transformations to the program in the testing data of the above-mentioned datasets. The number of original programs in our study is 2,088,411 and we used transformation to create 4,075,949 transformed programs. The types and number of applicable transformations vary from a program to another. Therefore, in our approach, different methods, based on the language features that they use, produce a different number of transformed programs.

Overall, the number of original programs with incorrect predictions is, on average, 2.4 times higher than the number of programs with correct predictions. Moreover, programs with incorrect predictions are amenable to, on average, 1.4 times more transformations. It may suggest that programs with correct predictions are smaller and simpler. In total, the number of transformed programs from the program with wrong initial predictions is much higher (3.4x and higher) than the number of transformed programs from programs with correct initial predictions.

5.5 Research Questions
In this paper, we seek to answer the following research questions.

- **RQ1** How do the transformations impact the prediction of neural program analyzers?
- **RQ2** When transformations are most effective in modifying the prediction of the neural program analyzers?
- **RQ3** How does method length impact the neural program analyzer’s generalizability?

6 RESULTS
6.1 RQ1: Impact of Transformation on the Models
Tables 2–7 show the changes of prediction for each transformation in all code2vec and code2seq neural program analyzers that we trained. Note that since the inputs to code2vec and code2seq are body of methods, we use terms methods and programs interchangeably, in this section. For each transformation, "# Original programs" denotes the number of programs eligible for the transformation, "# Transformed programs" denotes the number of transformed programs. Note that # Transformed programs can be larger than # Original programs, as a program may have more than one place where the transformation is applicable. “# Prediction changing programs” provides raw number of transformed programs that the prediction of neural program analyzer on the original and transformed program differ. “Prediction change(%)” denotes the percentage of transformed program that changed the output of the neural program analyzer.

code2vec is most sensitive to Permute Statement transformation on all datasets. On the other hand, the code2seq is most vulnerable to Switch to If, Variable Renaming, and Boolean Exchange transformation on JAVA-SMALL, JAVA-MED, and JAVA-LARGE dataset, respectively. Variable Renaming changes the text of terminals that change the embedding of path-context as well. However, Try-Catch Insertion and Unused Statement add some additional nodes and paths in AST. If models give less attention to those new paths, then the
Table 2: Change of prediction for code2vec on JAVA-SMALL dataset.

| Transformation       | # Original programs | # Transformed programs | # Prediction changing programs | Prediction change(%) |
|----------------------|---------------------|------------------------|-------------------------------|---------------------|
| Variable Renaming    | 31113               | 123123                 | 67622                        | 54.92               |
| Boolean Exchange     | 1158                | 1519                   | 818                          | 53.85               |
| Loop Exchange        | 3699                | 5160                   | 3064                         | 59.38               |
| Switch to If         | 246                 | 259                    | 178                          | 68.73               |
| Permute Statement    | 15325               | 74950                  | 53791                        | 71.77               |
| Try-Catch Insertion  | 32078               | 32078                  | 15039                        | 46.88               |
| Unused Statement     | 44426               | 44426                  | 17755                        | 39.97               |

Table 3: Change of prediction for code2vec on JAVA-MED dataset.

| Transformation       | # Original programs | # Transformed programs | # Prediction changing programs | Prediction change(%) |
|----------------------|---------------------|------------------------|-------------------------------|---------------------|
| Variable Renaming    | 235961              | 771208                 | 558984                        | 46.55               |
| Boolean Exchange     | 6407                | 8840                   | 4451                          | 50.35               |
| Loop Exchange        | 17107               | 23533                  | 14772                         | 62.77               |
| Switch to If         | 3312                | 3839                   | 2300                          | 59.91               |
| Permute Statement    | 88865               | 366640                 | 232054                        | 63.26               |
| Try-Catch Insertion  | 232769              | 232769                 | 99878                         | 42.91               |
| Unused Statement     | 351621              | 351621                 | 125880                        | 35.8                |

change is less effective. The Unused Statement and Try-Catch Insertion keep the existing AST mostly intact, consequently, in most cases, the average percentage of changes in prediction of Unused Statement and Try-Catch Insertion is comparatively less than other transformations.

“Total” column in Tables 2–7 supports that Permute Statement is more powerful than Variable Renaming in code2vec model whereas Variable Renaming is more effective than Permute Statement to code2seq model on all datasets. The real-value embeddings of paths are different for code2vec# and code2seq. In code2vec, an embedding matrix is initialized randomly for paths and learned during training, that contains rows that are mapped to each of the AST paths. On the other hand, in code2seq, each node of path comes from a learned embedding matrix and then a bi-directional LSTM is used to encode each of the AST paths separately. The bi-directional LSTM reads the path once from beginning to the end (as original order) and once from end to beginning (in reverse order). Therefore, the order change by Permute Statement becomes less sensitive in code2seq than code2vec.

Additionally, the Loop Exchange seems more effective than Switch to If on JAVA-MED and JAVA-LARGE dataset, but turned opposite on JAVA-SMALL dataset, for all models. Moreover, the Boolean Exchange shows poor performance on JAVA-SMALL and JAVA-MED dataset, but becomes comparatively more effective on JAVA-LARGE dataset, for all models. Another observation is that almost in all cases, the percentage of prediction change for all transformations are higher on JAVA-SMALL dataset, and then significantly drops on JAVA-MED and JAVA-LARGE dataset, respectively.

Observation 1: code2vec is most sensitive to Permute Statement transformation on all datasets. On the other hand, the code2seq is most vulnerable to Switch to If, Variable Renaming, and Boolean Exchange transformation on JAVA-SMALL, JAVA-MED, and JAVA-LARGE dataset, respectively.

6.2 RQ2: When Transformations are most Effective?

6.2.1 Single place transformation vs All place transformation. In our analysis, thus far, if a program has multiple candidates for a transformation, say n candidates, for transformation, we only apply them one at the time and end up with n distinct programs. We call this single-place transformation. Alternatively, we can replace all the candidate in a single transformation, and end up with one transformed program for each transformation per program. We call
Table 4: Change of prediction for code2vec on JAVA-LARGE dataset.

| Transformation         | # Original programs | Total       | Prediction change(%) |
|------------------------|---------------------|-------------|----------------------|
| Variable Renaming      |                     | 252725      | 42.06                |
|                        | # Transformed programs | 12107      |                       |
|                        | # Prediction changing programs | 5787       | 47.8                 |
| Boolean Exchange       |                     | 8868        |                       |
|                        | # Transformed programs | 49665       |                       |
|                        | # Prediction changing programs | 23104     | 46.52                |
| Loop Exchange          |                     | 35565       |                       |
|                        | # Transformed programs | 10478       |                       |
|                        | # Prediction changing programs | 3386     | 30.33                |
| Switch to If           |                     | 98669       |                       |
|                        | # Transformed programs | 428263      |                       |
|                        | # Prediction changing programs | 243574   | 56.87                |
| Permute Statement      |                     | 427092      |                       |
|                        | # Transformed programs | 247092      |                       |
|                        | # Prediction changing programs | 88690    | 35.86                |
| Try-Catch Insertion    |                     | 370927      |                       |
|                        | # Transformed programs | 370927      |                       |
|                        | # Prediction changing programs | 115781  | 31.21                |

Table 5: Change of prediction for code2seq on JAVA-SMALL dataset.

| Transformation         | # Original programs | Total       | Prediction change(%) |
|------------------------|---------------------|-------------|----------------------|
| Variable Renaming      |                     | 31113       |                       |
|                        | # Transformed programs | 123123      |                       |
|                        | # Prediction changing programs | 70371     | 57.16                |
| Boolean Exchange       |                     | 1158        |                       |
|                        | # Transformed programs | 1519        |                       |
|                        | # Prediction changing programs | 825       | 34.31                |
| Loop Exchange          |                     | 3699        |                       |
|                        | # Transformed programs | 5160        |                       |
|                        | # Prediction changing programs | 2711     | 52.54                |
| Switch to If           |                     | 246         |                       |
|                        | # Transformed programs | 259         |                       |
|                        | # Prediction changing programs | 160      | 61.78                |
| Permute Statement      |                     | 15325       |                       |
|                        | # Transformed programs | 74950       |                       |
|                        | # Prediction changing programs | 42685    | 56.95                |
| Try-Catch Insertion    |                     | 32078       |                       |
|                        | # Transformed programs | 32078       |                       |
|                        | # Prediction changing programs | 15490   | 48.29                |
| Unused Statement       |                     | 44426       |                       |
|                        | # Transformed programs | 44426       |                       |
|                        | # Prediction changing programs | 20257    | 45.6                 |

Observation 2: All-place transformation is more likely to induce changes in the predictions than sing-place transformations.

6.2.2 Correctly predicted methods vs Incorrectly predicted methods. Figure 4 depicts the changes in prediction after prediction on correctly vs. incorrectly predicted methods in all neural program analyzers. In code2vec neural program analyzers, the percentage of prediction changes after transformation in the correctly predicted methods ranges from 10.45% to 42.86%, while, in the incorrectly predicted methods, a larger portion of transformations, 38.18% to 73.25%, change the prediction of code2vec. In code2seq neural program analyzers, while the percentages of changes in predictions after transformation on the correctly predicted methods ranges from 9.19% to 36.36%, the percentages range from 44.18% to 62.9% in the incorrectly predicted methods.

Observation 3: The changes in prediction happens more frequently in the originally incorrect methods.

this all-place transformation. In the next experiment, we evaluate the generalizability of neural program analyzers under all-place transformation for the following transformations: Loop Exchange, Variable Renaming, Boolean Exchange, and Switch to If. Note that the all-place transformation is not applicable to Permute Statement, Try-Catch Insertion, and Unused Statement transformations, as we apply the Permute Statement transformation on a pair of statements and the Try-Catch Insertion and Unused Statement on a randomly selected statement.

Figure 3 compares the impact of single-place transformation and all-place transformation on the change of prediction in all neural program analyzers that we studied. For the code2vec model, the percentage of prediction change for all-place transformation is higher than the single-place transformation by a good margin for all the cases. Similarly, for the code2seq model, the prediction change percentage for all-place transformation is higher than the single-place transformation by a good margin except for the case (Switch to If, JAVA-SMALL). After a closer examination of JAVA-SMALL dataset and Switch to If transformation, we observe that the number of transformed methods for all-place is only 13, which is too low to provide comparative insight.
6.3 RQ3: Impact of Method Length on Generalizability

An important metric of interest might be the generalizability in terms of the number of statements in the methods. Figure 5 depicts the relation between length of methods and percentage of prediction changes. In the figure, the "Number of statements in method" denotes the number of executable lines in the body of methods before transformation. The trend in the figure suggests that there is a direct correlation between the size of programs and the percentage of predication changes after transformation. Note that there are only a handful of programs larger than 500 lines, therefore their behavior in Figures 5-b and 5-e is an outlier and can be ignored.

For JAVA-SMALL dataset, the prediction change of models for all transformations is more superior when a method has around 100 statements and there is no method more than 500 statements.

For JAVA-MED dataset, the prediction change of models for all transformations is more superior when a method exceeds 100 statements but drops significantly once a method exceeds 500 statements, except for the code2vec model on Permute Statement transformation and the code2seq model on Loop Exchange transformation where the prediction change increases even method exceeds 500 statements.
### Table 6: Change of prediction for code2seq on JAVA-MED dataset.

| Transformation       | # Original programs | # Transformed programs | # Prediction changing programs | Prediction change(%) |
|----------------------|---------------------|------------------------|-------------------------------|----------------------|
| Variable Renaming    | 235961              | 771208                 | 375939                        | 48.75                |
| Boolean Exchange     | 6407                | 8840                   | 3952                          | 44.71                |
| Loop Exchange        | 17107               | 23533                  | 10659                         | 45.29                |
| Switch to If         | 3312                | 3839                   | 1597                          | 41.6                 |
| Permute Statement    | 88865               | 366840                 | 170619                        | 46.51                |
| Try-Catch Insertion  | 232769              | 232769                 | 91176                         | 39.17                |
| Unused Statement     | 351621              | 351621                 | 141511                        | 40.25                |

For JAVA-LARGE dataset, the prediction change of code2vec model for all transformations is more superior when a method exceeds 100 statements but drops significantly once a method exceeds 500 statements, except for the Permute Statement and Switch to If transformation where the prediction change increases even method exceeds 500 statements. On the other hand, the prediction change of code2seq model for all transformations is increasing whether method exceeds 500 statements.

As shown in Figure 5, most of the cases the models exhibit notable increases in prediction change for all transformations as the number of lines in the program increases.

**Observation 4:** There is a direct correlation between the size of methods and their susceptibility of changes in the prediction under transformations.

### Table 7: Change of prediction for code2seq on JAVA-LARGE dataset.

| Transformation       | # Original programs | # Transformed programs | # Prediction changing programs | Prediction change(%) |
|----------------------|---------------------|------------------------|-------------------------------|----------------------|
| Variable Renaming    | 252725              | 916565                 | 431311                        | 47.04                |
| Boolean Exchange     | 8868                | 12107                  | 6227                          | 31.43                |
| Loop Exchange        | 35565               | 49665                  | 21112                         | 42.51                |
| Switch to If         | 10478               | 11165                  | 35565                         | 29.08                |
| Permute Statement    | 98669               | 428263                 | 11165                         | 43.53                |
| Try-Catch Insertion  | 247092              | 247092                 | 98669                         | 37.44                |
| Unused Statement     | 370927              | 38025                  | 10478                         | 37.44                |

### Table 8: Detailed percentages of changes in code2seq (JAVA-LARGE).

| Transformation | CCP | CIP | WSP | WCP | WDP |
|----------------|-----|-----|-----|-----|-----|
| VN             | 14.54 | 4.69 | 38.42 | 2.32 | 40.03 |
| BX             | 10.14 | 2.92 | 38.42 | 2.92 | 45.59 |
| LX             | 18.87 | 4.29 | 23.82 | 2.3  | 37.71 |
| SF             | 52.25 | 5.28 | 28.88 | 2.8  | 20.99 |
| FS             | 14.77 | 2.7  | 41.7  | 2.82 | 38.0  |
| TC             | 24.17 | 3.33 | 40.47 | 2.1  | 29.93 |
| UN             | 26.57 | 5.95 | 35.99 | 1.81 | 29.68 |

Table 8 shows the full breakdown of percentage of changes after transformations in code2seq (JAVA-LARGE) for all transformed programs. Note that we only refer to the code2seq (JAVA-LARGE) model in this section for its highest F1 score showed in Table 1. In this table, CCP, CIP, WSP, WCP, and WWDPCIPWLCP calculate the percent of cases that the neural program analyzer’s prediction has switched from correct to incorrect. In 9% to 36% (average %18) of cases, the neural program analyzer switches from a correct prediction to a wrong one in code2seq (JAVA-LARGE). That stay the same after transformations, percentage of wrong predictions that become correct, percentage of wrong predictions that change to another wrong prediction after the transformation. CIP calculates the percent of cases that the neural program analyzer’s prediction has switched from correct to incorrect. In 9% to 36% (average %18) of cases, the neural program analyzer switches from a correct prediction to a wrong one in code2seq (JAVA-LARGE).
Observation 5: In less than 3% of cases, a transformation switches from a wrong prediction to correct prediction.

7 DISCUSSION

In this paper, we study the current state of generalizability in two neural program analyzers. Although limited, it provides interesting insights. In this section, we first discuss why neural networks have become a popular, or perhaps the de-facto, tool for processing programs, and what are the implications of using neural networks in processing source code.

Neural networks constitute a powerful class of machine learning models with a large hypothesis class. For instance, a multi-layer feed-forward network is called a universal approximator, meaning, it can essentially represent any function [16]. Unlike traditional learning techniques that require extensive feature engineering and tuning, deep neural networks facilitate representation learning. That is that they are capable of performing feature extraction out of the raw data completely on their own [23]. Given a sufficiently large dataset, neural networks with adequate capacity can substantially reduce the burden of feature engineering. Availability of a large number of code repositories makes data-driven program analysis a good application for neural networks. However, it is still unknown if neural networks are the best way to process programs [15] vs. [20].

Although the large hypothesis class of neural networks and feature learning make them very appealing to use, the complex models built by neural networks are still too difficult to understand and interpret. Therefore as we apply neural networks in program analysis, we should develop specialized tools and techniques to enhance its interpretability of neural program analyzers.

7.1 Are we there yet?

Are neural program analyzers ready for widespread use in program analysis? Our results suggest: not yet. The models that we experimented are brittle to even very small changes in the AST. A correct prediction of the neural program analyzers in 9.19% to 36.36% cases could change to an incorrect one. Although substantial progress has been made in developing neural program analyzers for various program analysis and processing tasks, the literature lacks techniques to rigorously evaluate the reliability of such techniques. The recent line of work by Nghi et al. [6] in interpretability of neural program analyzers, Rabin et al. [28] in testing them, and Yefet et al. [39] are much needed steps in a right direction.

7.2 Generalizability vs. Robustness

There is a substantial line of work on evaluating the robustness of neural networks especially in the domain of vision and pattern recognition [33]. The key insight in such domains is that small, imperceptible changes in input should not impact the result of output. While this observation can be true for domains such as vision, it might not be directly applicable to the discrete domain of neural program analyzers, since some minor changes to a program can...
drastically change the semantic and behavior of the program. Quantifying the imperceptibility of source code is our future research goal.

7.3 Code Representation

The performance of models used in neural program analyzers, such as ones used in this study, is relatively low compared to the performance of neural models in domains such as natural language understanding [30], text classification [22]. To improve their performance, we would need novel code representations that better capture interesting characteristics of program.

8 RELATED WORK

Robustness of neural networks There is a substantial line of work on robustness of AI systems in general and deep neural networks in particular. Szegedy et al. [33] is the first to discover deep neural networks are vulnerable to small perturbations that are imperceptible to human eyes. They developed the L-BFGS method for systematic generation of such adversarial examples. Goodfellow et al. [12] proposes a more efficient method, called Fast Gradient Sign Method that exploits the linearity of deep neural networks. Many following up works [7, 10, 21, 26] further demonstrated the severity of the robustness issues with a variety of attacking methods. While aforementioned approaches only apply to models for image classification, new attacks have been proposed that target models in other domains, such as natural language processing [18, 24, 40] and graphs [8, 41].

Automated verification research community has proposed techniques to offer guarantees for robustness of neural networks by adapting bounded model checking [31], abstract interpretation [11], and Satisfiability Modulo Theory [17].

Models of Code Early works directly adopted NLP models to discover textual patterns existed in the source code [13, 27]. Those methods unfortunately do not account for the structural information programs exhibit. Following approaches address this issue by generalizing from the abstract syntax trees [4, 5, 25]. As Graph Neural Networks (GNN) have been gaining increasing popularity due to its remarkable representation capacity, many works have leveraged GNN to tackle challenging tasks like program repair and bug finding, and obtained quite promising results [3, 9, 38]. In parallel, Wang et al. developed a number of models [34, 36, 37] that feed off the run time information for enhancing the precision of semantic representation for model inputs.

9 CONCLUSION

In this paper, we perform a large-scale, comprehensive evaluation on the generalizability of code2vec and code2seq. In particular, we apply semantics preserving program transformations to produce new programs on which we expect models to keep their original predictions. We find that such program transformations frequently sway the predictions of both models, indicating the serious generalization issues that could negatively impact the wider applications of deep neural networks in program analysis tasks. We believe our work can motivate the future research on training not only accurate but also robust deep models of code.

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