On the Generalizability of Neural Program Analyzers with respect to Semantic-Preserving Program Transformations

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ABSTRACT

With the prevalence of publicly available source code repositories to train deep neural network models, neural program analyzers can do well in source code analysis tasks such as predicting method names in given programs that cannot be easily done by traditional program analyzers. Although such analyzers have been tested on various existing datasets, the extent in which they generalize to unforeseen source code is largely unknown. Since it is impossible to test neural program analyzers on all unforeseen programs, in this paper, we propose to evaluate the generalizability of neural program analyzers with respect to semantic-preserving transformations: a generalizable neural program analyzer should perform equally well on programs that are of the same semantics but of different lexical appearances and syntactical structures. More specifically, we compare the results of various neural program analyzers for the method name prediction task on programs before and after automated semantic-preserving transformations. We use three Java datasets of different sizes and three state-of-the-art neural network models for code, namely code2vec, code2seq, and Gated Graph Neural Networks (GGNN), to build nine such neural program analyzers for evaluation. Our results show that even with small semantically preserving changes to the programs, these neural program analyzers often fail to generalize their performance. Our results also suggest that neural program analyzers based on data and control dependencies in programs generalize better than neural program analyzers based only on abstract syntax trees. On the positive side, we observe that as the size of training dataset grows and diversifies the generalizability of correct predictions produced by the analyzers can be improved too. Our results on the generalizability of neural program analyzers provide insights to measure their limitations and provide a stepping stone for their improvement.

KEYWORDS

neural models, code representation, model evaluation, program transformation, generalizability

1 INTRODUCTION

Abundance of publicly available source code repositories has enabled a surge in data-driven approaches to programs analysis tasks. Those approaches aim to discover common programming patterns for various downstream applications [2] that are not easily achievable via traditional program analysis techniques, e.g., prediction of data types in dynamically typed languages [19], detection of the variable naming issues [3], or repair of software defects [13]. 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 neural networks in program analysis tasks, giving rise to increasing uses of neural program analyzers.

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

A comprehensive understanding of the extent of generalizability of neural program analyzers would help developers to know when to use data-driven approaches and when to resort to traditional deductive methods of program analysis. It would also help researchers to focus their efforts on devising new techniques to alleviate the shortcomings of existing analyzers. Lack of knowledge about the limits of 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 [41] 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, preliminary studies in this field started to emerge; e.g., Rabin et al. [34] proposed the idea of testing neural program analyzers using semantic-preserving transformations, Bui et al. [9] measured the impact of a specific code fragment by deleting it from the original source code, Zhang et al. [46] proposed a sampling approach to generate adversarial examples for code classification models, and Compton et al. [11] showed that the obfuscation of variable names makes a model on source code more robust with less bias towards variable names. Yefet et al. [45] followed and proposed adversarial example generation for neural program analyzers using prediction attribution [38]. Ramakrishnan et al. [35] increased robustness of neural representation of code by adding semantically equivalent programs to the training data, and Bielik and Vechev [8] proposed an approach for increasing the robustness of neural program analyzer for type prediction based on finding prediction attribution, adversarial training, and refining source code representation. Although these studies share the similar ultimate goal of evaluating and improving the performance of neural program analyzers with respect to unseen programs, there is still a lack of systematic quantifiable metrics to measure the extent that the neural program analyzers can generalize to unseen programs, and it would not be fair either to evaluate a neural program analyzer against all possible unseen programs that it was not designed for.

**Goal.** In this paper, we attempt to understand the limits of generalizability of neural program analyzers by comparing their behavior before and after semantic-preserving program transformations; that is, how the results of a neural program analyzer generalize to a semantically-equivalent program. By limiting unseen programs to semantically equivalent ones and controlling the semantic-preserving program transformations, we are able to provide a fair, systematic, quantifiable metric for evaluating the generalizability of a neural program analyzer.

In this paper, we report the results of a study on the generalizability of three highly-cited neural program analyzers: code2vec [6], code2seq [5], and GNN [15]. To evaluate their generalizability, we transform programs in the original datasets to generate semantically-equivalent counterparts. We employ six semantic-preserving transformations that impact the structure of programs (i.e. abstract syntax trees) with varying degrees, ranging from common refactoring, e.g., variable renaming, to more intrusive changes such as changing for-loops to while-loops.

Our results suggest that all neural program analyzers evaluated in this study are highly sensitive to the semantic-preserving transformations; that is, the output of the analyzer would be different on transformed program compared to its output on the original program. This sensitivity remains an issue even in the cases of small changes to the programs, such as renaming variables or reordering independent statements in a basic block. Moreover, our results suggest that neural program analyzers (e.g., GNN) that encode data and control dependencies in programs generalize better than the analyzers that are solely based on abstract syntax trees, and in most cases the generalizability of a neural program analyzer can be improved with the growth in the size of training datasets.

The results of this study reveal that the generalizability of neural program analyzers is still far from ideal and require more attention from the research community to devise more generalizable models of source code, or designing pre-processing techniques, e.g. canonicalizing programs representations, to increase immunity of neural program analyzers to such program transformations.

**Contributions.** This paper makes the following contributions.

- We introduce the notion of generalizability with respect to semantic-preserving transformations for neural program analyzers.
- We perform a large-scale study to evaluate the generalizability of state-of-the-art neural program analyzers.
- We provide insights into the generalizability of existing neural program analyzers and discuss their practical implications.

## 2 MOTIVATING EXAMPLE & DEFINITION

We use code2vec [6] for exposition in this section. The code2vec [6] is a recent, highly-cited (120+ citations) neural program analyzer that predicts the name of a Java method given the body of the method. Such a neural program analyzer can assist developers in classification of methods, code similarity detection, and code search.

Figure 1 shows two semantically-identical methods that implement compareTo functionality. The only difference between them is in the name of one of the variables. The left snippet in Figure 1 uses other, while the code on the right uses var\(^0\). However, the code2vec outputs, i.e., predictions, 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 the predictions of code2vec rely much on the identifier names (e.g., other). This reliance would make code2vec susceptible to a common refactoring such as variable renaming, and would make it not generalize to the code snippets that are semantically the same, but are different syntactically, even under common transformations.

Lack of generalizability would lead to distrust in the neural program analyzers and hamper their wider adoption and application. If such neural program analyzers were to be deployed in the problem settings wherein higher levels of generalizability are required, e.g., malware detection and bug repair, it would be much better for the neural program analyzers to demonstrate a high level of generalizability with respect to certain metrics.

**Generalizability.** We define generalizability as the capability of a neural program analyzer to return the same results under semantic-preserving transformations.

In this paper, we differentiate generalizability from the term robustness that is commonly used in the neural network literature for two main reasons. First, robustness is usually defined in the

\(^1\)var\(^0\) is not an uncommon identifier name in Java as it appears in the training vocabulary of the datasets. At the time of writing, a search on the GitHub returns more than 73K Java classes that use this identifier.
face of adversarial examples that have security implications, while we do not generate adversarial examples. Second, robustness implies imperceptible differences in the two focal inputs (e.g., minor pixel changes in two images) that are hard to attain in a sparse domain such as source code; the program transformations used in this paper often lead to perceptible textual and syntactic changes in program code. We also note that our definition of generalizability differs from that used in [24] that evaluate the usefulness of a neural program analyzer in various downstream tasks. Moreover, the generalizability in this work, while related to, is not the same as neural robustness [39], as robustness requires imperceptible changes to input data that may be considered as adversarial examples and has implications in reliability and security. Although the impact of our transformations on the semantic of the program is imperceptible, the changes to the textual and syntactic structures of the program can be perceptible.

Together with clearly defined semantic-preserving program transformations and their change impact on the prediction results of neural program analyzers (cf. Section 4), we aim to provide a systematic quantifiable way to measure the generalizability of the neural program analyzers, and thus shed lights on their capabilities and limits for future improvement. With the extensibility of the program transformations and the measurements of their change impact, our evaluation approach may also be extended to measure the generalizability of neural program analyzers more comprehensively in the near future.

3 BACKGROUND

Most neural program analyzers use neural network classifiers at their core component 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 depends on three main factors: quality of data (i.e., source code for this study), the representation of data for the neural network, and the neural network characteristics and its training parameters.

Quality of the data is concerned with the representativeness of data, and proper cleaning and preprocessing of the data. Currently, most studies use open-source projects usually in mainstream programming languages, e.g., C#, Java, C, or JavaScript. The available datasets for these tasks are still very immature and not standardized, and their quality is somewhat unknown. For example, a recent study by Allamanis [1] showed that virtually all available datasets suffer from code duplication that can greatly impact the performance of neural program analyzers.

The second factor affecting the performance of neural program analyzers is source code representation. Since neural networks need to take vectors of numbers as direct inputs, source code embeddings are used to produce a vector representation of source code. The representation determines which program features to include and how they should 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 the programs.

The third factor impacting the performance of a neural program analyzer is the characteristics—e.g., type, topology, and hyper-parameters—of the neural networks it uses. There are numerous choices of network architectures each with different properties. Currently, the class of recurrent neural networks (e.g., LSTM) and graph neural networks are among the most popular architecture in neural program analyzers [5, 6, 15].

4 EVALUATION APPROACH

Our approach for evaluating neural program analyzers relies on a metamorphic relation that states: the outputs of a neural program analyzer should not differ on semantically-equivalent programs. To this end, the evaluation approach is divided into two main steps: (1) generating new programs using semantic-preserving transformations, and (2) comparing the outputs of an analyzer before and after the transformations to compute generalizability metrics. We describe these steps in the rest of this section.

4.1 Transformations

In this work, we only evaluate neural program analyzers that take a method body as their input, therefore, we use the following set of transformations that are applicable to method-level code to generate semantically-equivalent methods. This set includes transformations ranging from common refactoring like variable renaming to more intrusive ones like loop exchange. The goal is to evaluate the generalizability of neural program analyzers under a wide range of semantic-preserving changes to the structure of the method.
We define the following metrics.

- **Variable Renaming (VN)** is variable renaming refactoring that renames the name of a variable in the method. The new name of the variable will be in the form of `varN` for a value of `N` such that `N` has not been defined in the scope. VN is a widely-used refactoring in the methods.
- **Permute Statement (PS)** swaps two independent statements (i.e., with no dependence) in a basic block of the method.
- **Unused Statement (UN)** inserts an unused string declaration to a randomly selected basic block in the method. Unused variables in the methods are common malpractice by the developers.
- **Loop Exchange (LX)** replaces `for` loops with `while` loops or vice versa.
- **Switch to If (SF)** replaces a `switch` statement in the method 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 method to ensure a semantic equivalence of the transformed method with the original method.

Note that each transformation has different impact on the structure of methods as follows.

- The Variable Renaming transformation only changes the terminal values and does not affect the structure of the AST.
- The Permute Statement transformation does not change the nodes, rather it only reorders two subtrees in the AST.
- The Unused Statement transformation adds a few nodes into the AST which increases the number of paths.
- The Loop Exchange transformation extensively impacts the AST by removing and inserting nodes.
- The Switch to If transformation also impacts the AST of the method substantially by removing and inserting nodes.
- The Boolean Exchange transformation alters the value of `true` or `false` and modifies the structure of the AST by removing or inserting unary-not nodes.

### 4.2 Generalizability Metrics

In this study, we define a few metrics to measure an analyzer’s different results for transformed programs and thus to quantify the generalizability of the analyzer.

Specifically, suppose `M` denotes a set of methods, given a semantic-preserving program transformation `T` that takes a method and creates a set `M' = \bigcup_{m \in M} T(m)` of transformed methods, and a neural program analyzer `NPA : M \rightarrow L`, where `L` denotes a set of labels, maps methods to labels. We evaluate the generalizability of `NPA` with respect to transformation `T`, by comparing `NPA(m)` and `NPA(m')` for `m' \in T(m)` for `m \in M`. Ideally, the analyzer should produce the same results on both `m` and `m'`, that is `NPA(m) = NPA(m')`. We define the following metrics.

#### Precision Change Percentage

\[
PCP = \frac{|\{m' \in M' | NPA(m) \neq NPA(m')\}|}{|\{m' \in M'\}|} \times 100. \tag{1}
\]

The lower values of PCP for `NPA` would suggest higher a degree of its generalizability with respect to the transformation.

#### Types of Changes

- (1) a correct prediction remains correct after the transformation of the methods,
- (2) a correct prediction changes to a wrong prediction after the transformation,
- (3) a wrong prediction changes to a correct prediction,
- (4) a wrong predicted label remains the same after the transformation,
- (5) a wrong predicted label changes into a different, yet wrong label.

We use the following five metrics to denote the proportion of each of these cases in the experiments. CCP, CWP, WWSP, WCP, and WWDP respectively denote the percentage of correct predictions that stay correct, the percentage of correct predictions that become wrong, the percentage of wrong predictions that stay to the same wrong prediction after the transformation, the percentage of wrong predictions that become correct, and the percentage of wrong predictions that change to another wrong prediction after the transformation.

### 5 EXPERIMENTAL SETTING

#### 5.1 Subject Neural Program Analyzers

The task of method name prediction [4] has attracted some attention recently. We use three neural program analyzers for the task of method name prediction that uses different code representations and neural network characteristics. These are `code2vec` [6], `code2seq` [5], and `GGNN` [15].

`code2vec` [6] 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.

While `code2vec` uses monolithic path embeddings and only generates a single label at a time, the `code2seq` [5] model uses an encoder-decoder architecture to encode paths node-by-node and generate label as sequences at each step. In `code2seq`, 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.

In `GGNN` [15], a variety of semantic edges are added into the AST of a method body to make it become a graph, and the Gated Graph Neural Network (GGNN) is applied to encode such graphs [3]. The initial embedding for a node of the graph is the concatenation between the node type embedding and node token embedding. Then a fixed number of message passing steps are applied for a
node to aggregate the embeddings of its neighbors. The output of the GGNN encoder is then fed into a bi-directional LSTM decoder to generate the method name as a language model of sub-tokens [15].

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 perform the transformations. Therefore, we used the code2seq dataset for training neural program analyzers for the study. There are three Java datasets based on the GitHub projects: JAVA-SMALL, JAVA-MED, and JAVA-LARGE. These datasets are mutually exclusive sets of projects.

- 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 source code public for training and evaluating their models. For GGNN, the implementation of the network is available but the code graph generation is not; so we re-implement the step to generate graphs. We use the parser SrcSlice2, an extension of SrcML3, to produce data dependency edges among AST nodes for training GGNN.

We train each model with the configuration as described in their original papers on each of the three aforementioned datasets, and thus construct three code2vec, three code2seq, and three GGNN neural program analyzers.

Table 1 summarizes the characteristics of the trained models. While the performance of our trained models for code2seq is on par with to the ones reported in the corresponding paper [5], the performance of code2vec did not reach the performance reported in [6], perhaps due to the differences in the dataset. However, the performance of our trained code2vec models is similar to the one reported in [5]. For GGNN, the performance is reasonably different from what are reported in [15] for three main reasons: (1) the AST produced by our parser can be different, (2) extraction of some types of the semantic edges proposed in [15] requires expensive analysis of the methods, therefore, we implemented and included a subset (seven out of ten) of semantic edges into the AST when generating the graph, and (3) the datasets are different.

| 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     | 33.28  | 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    |
| GGNN    | JAVA-SMALL    | 49.12     | 47.18  | 48.59    |
|         | JAVA-MED      | 58.30     | 47.49  | 52.34    |
|         | JAVA-LARGE    | 60.76     | 50.32  | 55.23    |

5.4 Population of Transformed Programs

We use our own tool based on the JavaParser4 library to transform Java programs. Two authors were involved in the implementation, testing and code review. We have performed manual inspection of sample transformed programs to ensure correctness of the transformations.

We have applied the applicable transformations to the programs in the testing data of the three datasets mentioned in section 5.2. The number of original programs in our study is 1,415,116, and we have used transformation to create 2,822,810 transformed programs. The types and number of applicable transformations vary from a program to another. Therefore, in our approach, different programs, 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, 2.8 times higher than the number of programs with correct predictions.

In total, the number of transformed programs generated from the programs with incorrect initial predictions is much higher (4.2x and higher) than the number of transformed programs generated from the programs with correct initial predictions, which may suggest that programs with correct predictions may be smaller and simpler.

5.5 Research Questions

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

RQ1 How do the transformations impact the predictions of neural program analyzers?
RQ2 When do transformations affect neural analyzers the most?
RQ3 How does method length impact the neural program analyzer’s generalizability?
RQ4 What are trends in types of changes?

6 RESULTS

6.1 RQ1: Impact of Transformations on the Neural Program Analyzers

Table 2 shows the prediction changes percentage (PCP) of the neural program analyzers for each transformation and dataset. In this table, "Original methods" denotes the number of methods eligible for the corresponding transformation, "# Transformed methods"
Table 2: The summary change of prediction across all models, datasets, and transformations.

| Transformation | Dataset | #Original methods | #Transformed methods | Prediction change (%) (PCP) | code2vec | code2seq | GGN
|----------------|---------|-------------------|---------------------|----------------------------|---------|---------|-----|
| Variable Renaming | JAVA-SMALL | 31113 | 123123 | 54.92 | 57.16 | 28.17 |
|                  | JAVA-MED  | 235961 | 771208 | 46.55 | 48.75 | 35.96 |
|                  | JAVA-LARGE| 252725 | 916565 | 42.06 | 47.04 | 31.92 |
|                  |          |        |        | Weighted Average = | 44.85 | 48.46 | 33.39 |
| Boolean Exchange  | JAVA-SMALL| 1158 | 1519 | 53.85 | 54.31 | 29.37 |
|                  | JAVA-MED  | 6407 | 8840 | 50.35 | 44.71 | 33.74 |
|                  | JAVA-LARGE| 8868 | 12107 | 47.80 | 51.43 | 31.98 |
|                  |          |        |        | Weighted Average = | 49.21 | 48.98 | 32.50 |
| Loop Exchange     | JAVA-SMALL| 3699 | 5160 | 59.38 | 52.54 | 31.66 |
|                  | JAVA-MED  | 17107 | 23533 | 62.77 | 45.29 | 36.67 |
|                  | JAVA-LARGE| 35565 | 49665 | 46.52 | 42.51 | 31.75 |
|                  |          |        |        | Weighted Average = | 52.25 | 44.01 | 32.22 |
| Switch to If      | JAVA-SMALL| 246 | 259 | 68.73 | 61.78 | 31.45 |
|                  | JAVA-MED  | 3312 | 3839 | 59.91 | 41.60 | 34.73 |
|                  | JAVA-LARGE| 10478 | 11165 | 30.33 | 29.08 | 45.50 |
|                  |          |        |        | Weighted Average = | 38.42 | 32.78 | 44.82 |
| Permute Statement | JAVA-SMALL| 3397 | 9169 | 72.80 | 57.32 | 26.36 |
|                  | JAVA-MED  | 16150 | 44711 | 65.44 | 42.64 | 34.09 |
|                  | JAVA-LARGE| 21956 | 74973 | 64.38 | 41.93 | 26.32 |
|                  |          |        |        | Weighted Average = | 65.35 | 43.27 | 29.02 |
| Unused Statement  | JAVA-SMALL| 44426 | 44426 | 39.97 | 45.60 | 28.34 |
|                  | JAVA-MED  | 351621 | 351621 | 35.80 | 40.25 | 42.79 |
|                  | JAVA-LARGE| 370927 | 370927 | 31.21 | 37.44 | 35.67 |
|                  |          |        |        | Weighted Average = | 33.82 | 39.20 | 38.51 |

denotes the number of methods generated as the result of applying the corresponding transformations on the original methods, and “Prediction change(%)” denotes PCP as defined in Sec 4. “Weighted Average” provides the weighted average of PCP for each transformation and neural models. The bold values in the Table 2 highlight the minimum value of PCP for the transformations. Since a transformation can be applied in more than one place in a method body, the number of transformed methods can be larger than the number of original methods.

As Table 2 depicts, all neural program analyzers are susceptible to semantic-equivalent transformations; however, the impact of transformations on PCP differs among different neural networks and datasets. Overall, GGN is less prone to prediction changes; in 14 out of 18 cases, PCP in GGN is significantly less than code2vec and code2seq. Moreover, in four out of six transformations, the weighted average of PCP for GGN neural analyzers is lower than the rest.

Observation 1: In most cases, GGN is less susceptible to prediction changes under semantic-preserving transformations.

Within code2vec, code2seq, and GGN, the PCP trend varies for different transformations and datasets. code2vec is most sensitive to Permute Statement on all datasets. On the other hand, code2seq is most vulnerable to Switch to If in JAVA-SMALL, Variable Renaming in JAVA-MED, and Boolean Exchange in JAVA-LARGE. In GGN, Switch to If is the most powerful transformation on all datasets. In most cases, for code2vec and code2seq, the PCP for Unused Statement is comparatively less than the other transformations, except for code2seq in JAVA-LARGE where Switch to If is less sensitive. In GGN, Permute Statement is a comparatively less powerful transformation than others on all datasets. Overall, based on the weighted average, code2vec is most sensitive to Permute Statement and least sensitive to Unused Statement, code2seq is most sensitive to Boolean Exchange and least sensitive to Switch to If, and GGN is most sensitive to Switch to If and least sensitive to Permute Statement.

Based on the weighted average, GGN performs worst for Switch to If and Unused Statement transformations. These two transformations add some additional nodes and paths in the AST. For code2vec and code2seq, if models give less attention to those new paths, then the change is less effective. However, GNN works by using a message passing mechanism among the nodes with a limited number of passing steps. In Unused Statement, because there is some irrelevant information added into the code, the passing steps in GGN will capture this information and ignore other useful information, thus having a strong impact on the prediction results. In Switch to If, because the structure of the AST is modified by adding and removing nodes, and GGN is a node-based method, i.e., combining node information with message passing, thus the GGN is sensitive to node modification in the AST for Switch to If.

Table 2 also supports that, in most cases, Permute Statement is more powerful than Variable Renaming in code2vec model whereas Variable Renaming is more powerful than Permute Statement in code2seq model. The reason is that the real-value embeddings of AST 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 a 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 changes by Permute Statement become less sensitive to code2seq than code2vec.

Another observation is that, in most cases of code2vec and code2seq, the PCP of the transformations in JAVA-SMALL is high, and it is significantly lower on larger datasets, i.e., JAVA-MED, and JAVA-LARGE. In GGNN, the PCP of the transformations shows a different trend: lowest in JAVA-SMALL, in most cases, and highest in JAVA-MED.

6.2 RQ2: When Transformations Affect Neural Program Analyzers the Most?

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 transformed programs. We call this single-place transformation. Alternatively, we can apply the transformations to all candidate locations in the program simultaneously to create only one transformed program. We call this all-place transformation. We evaluated the generalizability of neural program analyzers under all-place transformation for the following transformations: Variable Renaming, Boolean Exchange, Loop Exchange, and Switch to If. Note that the all-place transformation is not applicable to Permute Statement and Unused Statement transformations, as we apply the Permute Statement on a pair of statements and the Unused Statement on a random statement.

Figure 2 compares the impact of single-place transformation and all-place transformation on the prediction changes in all neural program analyzers that we studied. For the code2vec model, the percentage of prediction change for the all-place transformation is higher than the single-place transformation by a good margin for all the cases. Similarly, for the code2seq model, the percentage of prediction change for the 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. For the GGNN model, the difference between all-place transformation and single-place transformation is relatively very small compared to the code2vec and code2seq models. Even for (Boolean Exchange, JAVA-SMALL + JAVA-MED), (Loop Exchange, JAVA-MED + JAVA-LARGE), and (Switch to If, JAVA-LARGE), the percentage of prediction changes for the single-place transformation is higher than the all-place transformation. The results suggest that the performance of GGNN under single-place transformations and all-place transformations is consistent.

6.2.2 Correctly predicted methods vs. Incorrectly predicted methods. Figure 3 depicts the changes in prediction after prediction on correctly vs. incorrectly predicted methods in all neural program analyzers. In the code2vec model, the percentage of changes in predictions 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 76%, change the prediction of code2vec. Similarly, in the code2seq model, the percentage of changes in predictions after transformation in the correctly predicted methods and in the incorrectly predicted methods ranges from 9.19% to 36.36% and 46.66% to 62.9%, respectively. However, in the GGNN model, while the percentage of changes in predictions after transformation on the correctly predicted methods ranges from 1.9% to 8.58%, the percentages range from 31.05% to 62.01% in the incorrectly predicted methods.

Observation 3: GGNN is more stable than code2vec and code2seq in the originally correct methods, and the changes in prediction happen more frequently in the originally incorrect methods for all models.

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 4 depicts the relation between the length of methods and the prediction changes percentage (i.e., PCP). In the figure, the "Number of statements in method" denotes the number of executable lines in the body of methods before the transformation.

As shown in Figure 4(a-f), in most cases, the code2vec and code2seq model exhibit notable increases in prediction change for all transformations and datasets as the number of lines in the program increases. However, looking at Figure 4(g-i), it seems that the GGNN model is insensitive to the number of lines in methods compared to the code2vec and code2seq model.

Observation 4: The code2vec and code2seq show notable increases in PCP as the length of methods grows, but PCP in GGNN seems to be insensitive to the length of methods.

6.4 RQ4: Trends in the Types of Changes

Table 3 shows the full breakdown of the proportion of different types of changes after the transformation of methods. In code2vec and code2seq, the value of CCP increases with increase in the size of datasets. It may suggest that with a larger dataset the neural analyzer can generalize the correct predictions better.

In addition, we calculate \( \frac{\text{CCP}_{\text{CP}}}{\text{CCP}_{\text{WP}}} \) to approximate the ratio of cases that the neural program analyzer’s prediction switches from correct to wrong after transformations with respect to all the cases whose initial predictions are correct. The ratio helps us to simplify the comparison of (in)generalizability across different models. On average, 23% and 20% of cases, the neural program analyzer switches from a correct prediction to a wrong one in code2vec and code2seq, respectively. In GGNN, on the other hand, this switch happens in less than 5% of transformations.

Similarly, \( \frac{\text{CCP}_{\text{WP}}}{\text{CCP}_{\text{CP}}} \) approximates the ratio of cases switching from a wrong prediction to a correct prediction after
transformations with respect to all the cases whose initial prediction are wrong. In code2vec and code2seq, a transformation switches from a wrong prediction to correct prediction in less than 3% of cases, however, this switch happens in around 1% of transformations for GGNN. Higher weights than that of CCP implies that transformations indeed reduce the overall performance of the neural program analyzers.

\textbf{Observation 5:} Transformations indeed decrease the overall performance of neural program analyzers, and they are more likely to change the correct prediction of analyzers based on code2vec and code2seq than that of GGNN-based analyzers, while the generalizability of code2vec and code2seq can be compensated by larger datasets more than GGNN.
In this paper, we study the current state of generalizability in neural program analyzers built on `code2vec`, `code2seq`, and `GGNN`. 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 that it can essentially represent any function [21]. Unlike traditional learning techniques that require extensive feature engineering and tuning, deep neural networks facilitate representation learning. That is, they are capable of performing feature extraction out of raw data on their own [28]. Given a sufficiently large dataset, neural networks with adequate capabilities can substantially reduce the burden of feature engineering. Availability of a large number of code repositories makes data-driven program analysis a good application of neural networks. However, it is still unknown if neural networks are the best way to process programs [20] vs. [25].

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 their interpretability, generalizability and robustness.
7.1 Generalizability vs. Interpretability vs. Robustness and Others
Interpretability studied in the literature may help to build more understandable neural networks, revealing the limits and strengths of the networks, and thus to some extent, it helps to evaluate and understand the generalizability of the networks. However, our study of generalizability with respect to program transformation provides a different perspective complement to interpretability; the approach may have the potential in the future to help identify interpretable code elements by measuring the impact of certain types of code transformations.

As mentioned in Section 2, there is a substantial line of work on evaluating the robustness of neural networks especially in the domain of vision and pattern recognition [39]. 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 and many other aspects of source code is our future research goal.

7.2 Are we there yet?
Are neural program analyzers ready for widespread use in program analysis? The neural analyzers in our experiments are brittle to even very small changes in the methods. The semantic-preserving transformations can change the outputs of the analyzers in 26% to 73% of cases. Although our findings are limited to only one task, they suggest caution. The literature lacks techniques for rigorous evaluation of neural program analyzers. The recent line of work by Nghi et al. [9] in interpretability of neural program analyzers, Rabin et al. [34] in testing them, and Yefet et al. [45] are much needed steps in a right direction.

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 [36], text classification [27]. To improve their performance, we would need novel code representations that better capture interesting characteristics of programs.

8 RELATED WORK
Robustness of Neural Networks. There is a substantial line of work on the robustness of artificial intelligence (AI) systems in general and deep neural networks in particular. Szegedy et al. [39] is the first to discover that deep neural networks are vulnerable to small perturbations that are imperceptible to human eyes. They developed the L-BFGS method for the systematic generation of such adversarial examples. Goodfellow et al. [17] proposes a more efficient method, called the Fast Gradient Sign Method that exploits the linearity of deep neural networks. Many following up works [10, 14, 26, 31] 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 [23, 29, 48] and graphs [12, 49].

The automated verification research community has proposed techniques to offer guarantees for the robustness of neural networks by adapting bounded model checking [37], abstract interpretation [16], and Satisfiability Modulo Theory [22]. Amershi et al. [7] study the challenges in developing AI solutions and Zhang et al. [47] survey testing of machine-learning systems.

Models of Code. Early works directly adopted NLP models to discover textual patterns existed in the source code [18, 33]. Those methods, unfortunately, do not account for the structural information programs exhibit. Following approaches address this issue by generalizing from the abstract syntax trees [5, 6, 30, 32]. 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, 13, 44]. In parallel, Wang et al. developed a number of models [40, 42, 43] that feed off the run time information for enhancing the precision of semantic representation for model inputs.

9 THREATS TO VALIDITY
There are various threats to the validity of our approach.

Limited Data and Evaluation Scope. We only evaluated the generalizability of neural program analyzers built on code2vec, code2seq, and GGN. for one task in Java programs. Therefore, our results may not generalize to other neural analyzers or other tasks or other programming languages. We leave the evaluation of the general applicability of our approach as future work.

Transformations. The proposed transformations in this paper impact program ASTs in varying degrees. Some of the transformations, e.g., variable renaming, are common refactoring techniques. However, these transformations may not represent many possible transformations in other domains. We will instantiate and extend our approach with other transformations from other domains.

Internal Validity. Some bugs may exist in the toolchain and neural analyzers implemented in this paper. To reduce the probability of bugs, two authors reviewed the code and manually inspected a sample of transformed programs to ensure the reliability of transformations.

10 CONCLUSION & FUTURE WORK
In this paper, we perform a large-scale, systematic evaluation of the generalizability of state-of-the-art neural program analyzers built on code2vec, code2seq, and GGN. In particular, we apply six semantic-preserving program transformations to produce new programs on which we expect the neural program analyzers to keep their original predictions. We find that such program transformations frequently sway the predictions of these analyzers, indicating serious generalization issues that could negatively impact the wider applications of deep neural networks in program analysis tasks. Although analyzers that encode more program dependency information and are trained with larger datasets may exhibit more generalizable behavior, their generalizability is still limited. We believe this work provides a systematic approach and metrics for evaluating neural program analyzers, and can motivate future research
on training not only accurate but also generalizable deep models of code. Future work that includes more semantic-preserving and even some semi-semantic-preserving transformations in our approach and adapts more fine-grained predication change metrics may further extend the applicability of our approach to various neural program analyzers designed for different tasks.

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