Graph Neural Networks For Mapping Variables Between Programs

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Abstract. Automated program analysis is a pivotal research domain in many areas of Computer Science — Formal Methods and Artificial Intelligence, in particular. Due to the undecidability of the problem of program equivalence, comparing two programs is highly challenging. Typically, in order to compare two programs, a relation between both programs’ sets of variables is required. Thus, mapping variables between two programs is useful for a panoply of tasks such as program equivalence, program analysis, program repair, and clone detection. In this work, we propose using graph neural networks (GNNs) to map the set of variables between two programs based on both programs’ abstract syntax trees (ASTs). To demonstrate the strength of variable mappings, we present three use-cases of these mappings on the task of program repair to fix well-studied and recurrent bugs among novice programmers in introductory programming assignments (IPAs). Experimental results on a dataset of 4166 pairs of incorrect/correct programs show that our approach correctly maps 83\% of the evaluation dataset. Moreover, our experiments show that the current state-of-the-art on program repair, greatly dependent on the current state-of-the-art on program repair, greatly dependent on the current state-of-the-art on program repair, greatly dependent on the current state-of-the-art on program repair, greatly dependent on

1 Introduction

The problem of program equivalence, i.e., deciding if two programs are equivalent, is undecidable \cite{33, 6}. On that account, the problem of repairing an incorrect program based on a correct implementation is very challenging. In order to compare both programs, i.e., the correct and the faulty implementation, program repair tools first need to find a relation between both programs’ sets of variables. Besides program repair \cite{1}, the task of mapping variables between programs is also important for program analysis \cite{10}, program equivalence \cite{8}, program clustering \cite{27, 39}, and clone detection \cite{15}.

Due to a large number of student enrollments every year in programming courses, providing feedback to novice students in introductory programming assignments (IPAs) requires substantial time and effort by the faculty \cite{41}. Hence, there is an increasing need for systems capable of providing automated, comprehensive, and personalized feedback to students in programming assignments \cite{12,10,11,1}. Semantic program repair has become crucial to provide feedback to each novice programmer by checking their IPAs submissions using a pre-defined test suite. Semantic program repair frameworks use a correct implementation, provided by the lecturer or submitted by a previously enrolled student, to repair a new incorrect student’s submission. However, the current state-of-the-art tools on semantic program repair \cite{10, 1} for IPAs have two main drawbacks: (1) require a perfect match between the control flow graphs (loops, functions) of both programs, the correct and the incorrect one; and (2) require a bijective relation between both programs’ sets of variables. Hence, if one of these requirements is not satisfied, then, these tools cannot fix the incorrect program with the correct one.

For example, consider the two programs presented in Figure 1. These programs are students’ submissions for the IPA of printing all the natural numbers from 1 to a given number \(n\). The program in Listing 1 is a semantically correct implementation that uses a for-loop to iterate all the natural numbers until \(n\). The program in Listing 2 uses a while-loop and an auxiliary function. This program is semantically incorrect since the student forgot to initialize the variable \(j\), a frequent bug among novice programmers called missing expression/assignment \cite{35}. However, in this case, state-of-the-art program repair tools \cite{10, 1} cannot fix the buggy program, since the control flow graphs do not match either due to using different loops (for-loop vs. while-loop) or due to the use of an auxiliary function. Thus, these program repair tools cannot leverage on the correct implementation in Listing 1 to repair the faulty program in Listing 2.

To overcome these limitations, in this paper, we propose a novel graph program representation based on the structural information of the abstract syntax trees (ASTs) of imperative programs to learn how to map the set of variables between two programs using graph neural networks (GNNs). Additionally, we present use-cases of program repair where these variable mappings can be applied to repair common bugs in incorrect students’ programs that previous tools are not always capable of handling. For example, consider again the two programs presented in Figure 1. Note that having a mapping between both programs’ variables (e.g., \(\{n: l; i: j\}\)) lets us reason about, on the level of expressions, which program fixes one can perform on the faulty program in Listing 2. In this case, when comparing variable \(i\) with variable \(j\) one would find the missing assignment i.e., \(j = 1\).
Listing 1: A semantically correct student’s implementation.

```c
int main(){
    int n, l;
    scanf("%d", &n);
    for(i = 1; i <= n; i++){
        printf("%d\n", i);
    }
    return 0;
}
```

Listing 2: A semantically incorrect student’s implementation since the variable `j` in the `main` function is not initialized.

```c
void loop(int j, int l){
    while (l >= j){
        printf("%d\n", j);
        ++j;
    }
    }

int main(){
    int j, l;
    scanf("%d", &l);
    loop(j, l);
    return 0;
}
```

Another useful application for mapping variables between different programs is fault localization. There is a body of research on fault localization [10, 21, 22, 23], that requires the usage of assertions in order to verify programs. Variable mappings can be helpful in sharing these assertions among different programs. Additionally, several program repair techniques (e.g., SEARCHREPAIR [13], CLARA [10]) enumerate all possible mappings between two programs’ variables during the search for possible fixes, using a correct program [10] or code snippets from a database [13]. Thus, variable mappings can drastically reduce the search space, by pruning all the other solutions that use a different mapping.

In programming courses, unlike in production code, typically, there is a reference implementation for each programming exercise. This comes with the challenge of comparing different names and structures between the reference implementation and a student’s program. To deal with this challenging task, we propose to map variables between programs using GNNs. Therefore, we explore three tasks to illustrate the advantages of using variable mappings to repair some frequent bugs without considering the incorrect/correct programs’ control flow graphs. Hence, we propose to use our variable mappings to fix bugs of: wrong comparison operator, variable misuse, and missing expression. These bugs are recurrent among novice programmers [35] and have been studied by prior work in the field of automated program repair [3, 51, 57, 54].

Experiments on 4166 pairs of incorrect/correct programs show that our GNN model correctly maps 83% of the evaluation dataset. Furthermore, we also show that previous approaches can only repair about 72% of the dataset, mainly due to control flow mismatches. On the other hand, our approach, solely based on variable mappings, can fix 88.5%.

The main contributions of this work are:

- A novel graph program representation that is agnostic to the names of the variables and for each variable in the program contains a representative variable node that is connected to all the variable’s occurrences;
- We propose to use GNNs for mapping variables between programs based on our program representation, ignoring the variables’ identifiers;
- Our GNN model and the dataset used for this work’s training and evaluation, will be made open-source and publicly available on GitHub: https://github.com/pmorvalho/ecai23-GNNs-for-mapping-variables-between-programs.

Figure 1: Two implementations for the IPA of printing all the natural numbers from 1 to a given number `n`. The program in Listing 2 is semantically incorrect since the variable `j`, which is the variable being used to iterate over all the natural numbers until the number `n`, is not being initialized, i.e., the program has a bug of `missing expression`. The mapping between these programs’ sets of variables is `{n: 1; i: j}`.

The structure of the remainder of this paper is as follows. First, Section 2 presents our graph program representations. Next, Section 3 describes the GNNs used in this work. Section 4 introduces typical program repair tasks, as well as our program repair approach using variable mappings. Section 5 presents the experimental evaluation where we show the effectiveness of using GNNs to produce correct variable mappings between programs. Additionally, we compare our program repair approach based on the variable mappings generated by the GNN with state-of-the-art program repair tools. Finally, Section 6 describes related work, and the paper concludes in Section 7.

2 Program Representations

We represent programs as directed graphs so the information can propagate in both directions in the GNN. These graphs are based on the programs’ abstract syntax trees (ASTs). An AST is described by a set of nodes that correspond to non-terminal symbols in the programming language’s grammar and a set of tokens that correspond to terminal symbols [14]. An AST depicts a program’s grammatical structure [2]. Figure 2a shows the AST for the small code snippet presented in Listing 3.

Regarding our graph program representation, firstly, we create a unique node in the AST for each distinct variable in the program and connect all the variable occurrences in the program to the same unique node. Figure 2b shows our graph representation for the small code snippet presented in Listing 3. Observe that our representation uses a single node for each variable in the program, the green nodes `a` and `b`. Moreover, we consider five types of edges in our representation: child, sibling, read, write, and chronological edges. Child edges correspond to the typical edges in the AST representation that connect each parent node to its children. Child edges are bidirectional in our representation. In Figure 2c, the black edges correspond to child edges. Sibling edges connect each child to its sibling successor. These edges denote the order of the arguments for a given node and have been used in other program representations [3]. Sibling edges allow the program representation to differentiate between different arguments when the order of the arguments is important (e.g. binary operation such as `≤`). For example, consider the node that corresponds to the operation `σ(A1, A2, . . . , An)`. The parent node `σ` is connected to each one of its children by a child edge e.g. `σ ⇔ A1, σ ⇔ A2, . . . , σ ⇔ An`. Additionally, each child its connected to its successor by a sibling edge e.g.
Listing 3: Small example of a C code block with an expression.

```c
1  { // a and b are ints
2      a = a - b;
3  }
```

Figure 2: AST and our graph representation for the small code snippet presented in Listing 3.

A₁ → A₂, A₂ → A₃, ..., Aₙ₋₁ → Aₙ. In Figure 2b, the red dashed edges correspond to sibling edges.

Regarding the write and read edges, these edges connect the ID nodes with the unique nodes corresponding to some variable. Write edges are connections between an ID node and its variable node. This edge indicates that the variable is being written. Read edges are also connections between an ID node and its variable node, although these edges indicate that the variable is being read. In Figure 2b, the blue dashed edge corresponds to a write edge while the green dashed edges correspond to read edges. Lastly, chronological edges establish an order between all the ID nodes connected to some variable. These edges denote the order of the ID nodes for a given variable node. For example, in Figure 2b, the yellow dashed edge corresponds to a chronological edge between the ID nodes of the variable a. Besides the siblings and the chronological edges, all the other edges are bidirectional in our representation.

The novelty of our graph representation is that we create a unique variable node for each variable in the program and connect each variable’s occurrence to its unique node. This lets us map two variables in two programs, even if their number of occurrences is different in each program. Furthermore, the variable’s identifier is suppressed after we connect all the variable’s occurrences to its unique node. This way, all the variables’ identifiers are anonymized. Prior work on representing programs as graphs [3, 37, 4] use different nodes for each variable occurrence and take into consideration the variable identifier in the program representation. Furthermore, to the best of our knowledge, combining all five types of edges (sibling, write, read, chronological, and AST) is also novel. Section 5.3 presents an ablation study on the set of edges to analyze the impact of each type of edge.

3 Graph Neural Networks (GNNs)

Graph Neural Networks (GNNs) are a subclass of neural networks designed to operate on graph-structured data [20], which may be citation networks [7], mathematical logic [9] or representations of computer code [3]. Here, we use graph representations of a pair of ASTs, representing two programs for which we want to match variables, as the input. The main operative mechanism is to perform message passing between the nodes, so that information about the global problem can be passed between the local constituents. The content of these messages and the final representation of the nodes is parameterized by neural network operations (matrix multiplications composed with a non-linear function). For the variable matching task, we do the following to train the parameters of the network. After several message passing rounds through the edges defined by the program representations above, we obtain numerical vectors corresponding to each variable node in the two programs. We compute scalar products between each possible combination of variable nodes in the two programs, followed by a softmax function. Since the program samples are obtained by program mutation, the correct mapping of variables is known. Hence, we can compute a cross-entropy loss and minimize it so that the network output corresponds to the labeled variable matching. Note that the network has no information on the name of any object, which means that the task must be solved purely based on the structure of the graph representation. Therefore, our method is invariant to the consistent renaming of variables.

Architecture Details. The specific GNN architecture used in this work is the relational graph convolutional neural network (RGCN), which can handle multiple edges or relation types within one graph [34]. The numerical representation of nodes in the graph is updated in the message passing step according to the following equation:

\[ x'_i = \Theta_{\text{node}} \cdot x_i + \sum_{r \in \mathcal{R}} \sum_{j \in \mathcal{N}_r(i)} \frac{1}{|\mathcal{N}_r(i)|} \Theta_r \cdot x_j, \]

where \( \Theta \) are the trainable parameters, \( \mathcal{R} \) stands for the different edge types that occur in the graph, and \( \mathcal{N}_r(i) \) the neighbouring nodes of the current node \( i \) that are connected with the edge type \( r \) [32]. After each step, we apply Layer Normalization [3] followed by a Rectified Linear Unit (ReLU) non-linear function.

We use two separate sets of parameters for the message passing phase for the program with the bug and the correct program. Five message passing steps are used in this work. After the message passing phase, we obtain numerical vectors representing every node in both graphs. We then calculate dot products \( \bar{a} \cdot \bar{b} \) between the vectors representing variable nodes in the buggy program graph \( a \in A \) and the variable nodes from the correct graph \( b \in B \), where \( A \) and \( B \)
are the sets of variable node vectors. A score matrix $S$ with dimensions $|A| \times |B|$ is obtained, to which we apply the softmax function on each row to obtain the matrix $P$. The values in each row of $P$ can now be interpreted as representing the probability that variable $a_i$ maps to each of the variables $b_j$.

4 Use-Cases: Program Repair

In this section, we propose a few use-cases on how to use variable mappings for program repair. More specifically, to repair bugs of: wrong comparison operator, variable misuse, and missing expressions. These bugs are common among novice programmers and have been studied by prior work in the field of automated program repair. The current state-of-the-art on semantic program repair tools focused on repairing IPAS, such as CLARA [10] and VERIFIX [1], are only able to fix these bugs if the correct expression in the correct program is located in a similar program structure as the incorrect expression in the incorrect implementation. For example, consider again the two programs presented in Figure 5. If the loop condition was incorrect in the faulty program, CLARA and VERIFIX could not fix it, since the control flow graphs do not match. Thus, these tools would fail due to structural mismatch.

The following sections present three program repair tasks that take advantage of variable mappings to repair an incorrect program using a correct implementation for the same IPA without considering the programs’ structures. Our main goal is to show the usefulness of variable mappings. We claim that variable mappings are informative enough to repair these realistic types of bugs. Given a buggy program, we search for and try to repair all three types of bugs. Whenever we find a possible fix, we check if the program is correct using the IPA’s test suite.

**Bug #1: Wrong Comparison Operator (WCO).** Our first use-case are faulty programs with the bug of wrong comparison operator (WCO). This is a recurrent bug in students’ submissions to IPAs since novice programmers frequently use the wrong operator, e.g., $i <= n$ instead of $i < n$.

We propose tackling this problem solely based on the variable mapping between the faulty and correct programs, ignoring the programs’ structure. First, we rename all the variables in the incorrect program based on the variable mapping by changing all the variables’ identifiers in the incorrect program with the corresponding variables’ identifiers in the correct implementation. Second, we count the number of times each comparison operation appears with a specific pair of variables/expressions in each program. Then, for each comparison operation in the correct program, we compute the mirrored expression, i.e., swapping the operator by its mirrored operator, and swapping the left-side and right-side of the operation. This way, if the incorrect program has the same correct mirrored expression, we can match it with an expression in the correct program. For example, in the programs shown in Figure 5, both loop conditions would match even if they are mirrored expressions, i.e., $i <= n$ and $n >= i$.

Afterwards, we iterate over all the pairs of variables/expressions that appear in comparison operations of the correct program (plus the mirrored expressions) and compare if the same pair of variables/expressions appear the same number of times in the incorrect program, using the same comparison operator. If this is not the case, we try to fix the program using the correct implementation’s operator in each operation of the incorrect program with the same pair of variables/expressions. Once the program is fixed, we rename all the variables based on the reverse variable mapping.

**Bug #2: Variable Misuse (VM).** Our second program repair task are buggy programs with variables being misused, i.e., the student uses the wrong variable in some program location. The wrong variable is of the same type as the correct variable that should be used. Hence, this bug does not produce any compilation errors. This type of bug is common among students and experienced programmers. The task of detecting this specific bug has received much attention from the Machine Learning (ML) research community.

Once again, we propose to tackle this problem based on the variable mapping between the faulty program and the correct one, ignoring the programs’ structure. We start by renaming all the variables in the incorrect program based on the variable mapping. Then we count the number of times each variable appears in both programs. If a variable, $x$, appears more times in the incorrect program than in the correct implementation, and if another variable $y$ appears more times in the correct program, then we try to replace each occurrence of $x$ in the incorrect program with $y$. Once the program is fixed, we rename all the variables based on the reverse variable mapping.

**Bug #3: Missing Expression (ME).** The last use-case we will focus on is to repair the bug of missing expressions/assignments. This bug is also recurrent in students’ implementations of IPAs. Frequently, students forget to initialize some variable or to increment a variable of some loop, resulting in a bug of missing expression. However, unlike the previously mentioned bugs, this one has not received much attention from the ML community since it is more complex to repair this program fault. To search for a possible fix, we start by renaming all the variables in the incorrect program based on the variable mapping. Next, we count the number of times each expression appears in both programs. Expressions that appear more frequently in the correct implementation are considered possible repairs. Then, we try to inject these expressions, one at a time, into the incorrect implementation’s code blocks and check the program’s correctness. Once the program is fixed, we rename all the variables based on the reverse variable mapping. This task is solely based on the variable mapping between the faulty and the correct programs.

5 Experiments

**Experimental Setup.** We trained the Graph Neural Networks on an (Intel(R) Xeon(R) Gold 6140 CPU @ 2.30GHz server with 72 CPUs and 692GB RAM. Networks were trained using NVIDIA GEFORCE GTX 1080 graphics cards with 12GB of memory. All the experiments related to our program repair tasks were conducted on an Intel(R) Xeon(R) Silver computer with 4210R CPUs @ 2.40GHz, using a memory limit of 64GB and a timeout of 60 seconds.

5.1 IPAS Dataset

To evaluate our work, we used C-PACK-IPAS, a benchmark of student programs developed during an introductory programming course in the C programming language for ten different IPAS, over two distinct academic years, at Instituto Superior Técnico. These IPAS are small imperative programs that deal with integers and input-output operations. First, we selected a set of correct submissions, i.e., programs that compiled without any error and satisfied a set of input-output test cases for each IPA. We gathered 238 correct students’ submissions from the first year and 78 submissions from the second year. We used the students’ submissions from the first
the real mappings and our GNN’s variable mappings. To generate this dataset, we used MULTI-IPAS [28], a program modifier capable of mutating C programs syntactically, generating semantically equivalent programs, i.e., changing the program’s structure but keeping its semantics. There are several program mutations available in MULTI-IPAS: mirroring comparison expressions, swapping the if’s then-block with the else-block and negating the test condition, increment/decrement operators mirroring, variable declarations reordering, translating for-loops into equivalent while-loops, and all possible combinations of these program mutations. Hence, MULTI-IPAS has thirty-one different configurations for mutating a program. All these program mutations generate semantically equivalent programs. Afterwards, we also used MULTI-IPAS, to introduce bugs into the programs, such as wrong comparison operator (WCO), variable misuse (VM), missing expression (ME). Hence, we gathered a dataset of pairs of programs and the mappings between their sets of variables [30]. Each pair corresponds to a real correct student’s implementation, and the second program is the student’s program after being mutated and with some bug introduced. Thus, this IPA dataset is generated, although based on real programs. The dataset is divided into three different sets: training set, validation set, and evaluation set. The programs generated from first year submissions are divided into a training and validation set based on which students’ submissions they derive from. 80% of the students supply the training data, while 20% supply validation data. The evaluation set, which is not used during the machine learning optimization, is chronologically separate: it consists only of second year submissions, to simulate the real-world scenario of new, incoming students. The training set is composed of 3372, 5170, and 2908 pairs of programs from the first academic year for the WCO, VM, and ME bugs, respectively. The validation set, which was used during development to check the generalization of the prediction to unseen data, comprises 1457, 1457, and 1023 pairs of programs from the first year. Note that we subsample from the full spectrum of possible mutations, to keep the training data size small enough to train the network with reasonable time constraints. From each of the 31 combinations of mutations, we use one randomly created sample for each student per exercise. We found that this already introduced enough variation in the training dataset to generalize to unseen data. Finally, the evaluation set is composed of 4166 pairs of programs from the second year (see 3rd row, Table [3]). This dataset will be publicly available for reproducibility reasons.

### 5.2 Training

At training time, since the incorrect program is generated, the mapping between the variables of both programs is known. The network is trained by minimizing the cross entropy loss between the labels (which are categorical integer values indicating the correct mapping) and the values in each corresponding row of the matrix $P$. As an optimizer, we used the Adam algorithm with its default settings in PyTorch [19]. The batch size was 1. As there are many different programs generated by the mutation procedures, we took one sample from each mutation for each student. Each network was trained for 20 full passes (epochs) over this dataset while shuffling the order of the training data before each pass. For validation purposes, data corresponding to 20% of the students from the first year of the dataset was kept separate and not trained on.

Table 1 shows the percentage of validation data mappings that were exactly correct (accuracy) after 20 epochs of training, using four different GNN models. Each GNN model was trained on programs with the bugs of wrong comparison operator (WCO), variable misuse (VM), missing expression (ME) or all of them (All). Furthermore, each GNN model has its own validation set with programs with a specific type of bug. The GNN model trained on All Bugs was validated using a mix of problems from each bug type. In the following sections, we focus only on this last GNN model (All Bugs).

### 5.3 Evaluation

Our GNN model was trained on programs with bugs of wrong comparison operator (WCO), variable misuse (VM), and missing expression (ME). We used two evaluation metrics to evaluate the variable mappings produced by the GNN. First, we counted the number of totally correct mappings our GNN was able to generate. We consider a variable mapping totally correct if it correctly maps all the variables between two programs. Secondly, we computed the overlap coefficient between the original variable mappings and the variable mappings generated by our GNN. The overlap coefficient is a similarity metric given by the intersection between the two mappings divided by the length of the variable mapping.

The first row in Table 2 shows the number of totally correct variable mappings computed by our GNN model. One can see that the GNN maps correctly around 83% of the evaluation dataset. We have

<table>
<thead>
<tr>
<th>Evaluation Metric</th>
<th>WCO Bug</th>
<th>VM Bug</th>
<th>ME Bug</th>
<th>All Bugs</th>
</tr>
</thead>
<tbody>
<tr>
<td># Correct Mappings</td>
<td>87.38%</td>
<td>81.87%</td>
<td>79.95%</td>
<td>82.77%</td>
</tr>
<tr>
<td>Avg Overlap Coefficient</td>
<td>96.99%</td>
<td>94.28%</td>
<td>94.51%</td>
<td>95.05%</td>
</tr>
<tr>
<td># Programs</td>
<td>1078</td>
<td>1936</td>
<td>1152</td>
<td>4166</td>
</tr>
</tbody>
</table>

Table 1: Evaluation mappings fully correct after 20 training epochs.

Table 2: The number of correct variable mappings generated by our GNN on the evaluation dataset and the average overlap coefficients between the real mappings and our GNN’s variable mappings.
also looked into the number of variables in the mappings we were not getting entirely correct. The results showed that programs with more variables (e.g., six or seven variables) are the most difficult for our GNN to map their variables correctly (see [10]). For this reason, we have also computed the overlap coefficient between the GNN’s variable mappings and the original mappings (ground truth). The second row in Table 2 shows the average of the overlap coefficients between the original variable mappings and the mappings generated by our GNN model. The overlap coefficient [8] measures the intersection (overlap) between two mappings. If the coefficient is 100%, both sets are equal. One set cannot be a subset of the other since both sets have the same number of variables in our case. The opposite is 0% overlap, meaning there is no intersection between the two mappings. The GNN achieved at least 94% of overlap coefficients, i.e., even if the mappings are not always fully correct, almost 94% of the variables are correctly mapped by the GNN.

Ablation Study. To study the effect of each type of edge in our program representation, we have performed an ablation study on the set of edges. Prior works have done similar ablation studies [3], Table 3 presents the accuracy of our GNN (i.e., number of correct mappings) on the evaluation dataset after 20 epochs. We can see that the accuracy of our GNN drops from 96% to 53% if we remove the AST edges (index 0), which was expected since these edges provide syntactic information about the program. Removing the sibling edges (index 1) also causes a great impact on the GNN’s performance, dropping to 74%. The other edges are also important, and if we remove them, there is a negative impact on the GNN’s performance. Lastly, since the AST and sibling edges caused the greatest impact, we evaluated using only these edges on our GNN and got an accuracy of 94.7%. However, the model using all the proposed edges has the highest accuracy of 96.49%.

### 5.4 Program Repair

This section presents the results of using variable mappings on the three use-cases described in Section 4, i.e., the tasks of repairing bugs of: wrong comparison operator (WCO), variable misuse (VM) and missing expression (ME). For this evaluation, we have also used the two current publicly available program repair tools for fixing introductory programming assignments (IPAs): CLARA [10] and VERIFY [11]. Furthermore, we have tried to fix each pair of incorrect/correct programs in the evaluation dataset by passing each one of these pairs of programs to every repair method: VERIFY, CLARA, and our repair approach based on the GNN’s variable mappings.

If our repair procedure cannot fix the incorrect program using the most likely variable mapping according to the GNN model, then it generates the next most likely mapping based on the variables’ distributions computed by the GNN. Therefore, the repair method iterates over all variable mappings based on the GNN’s predictions. Lastly, we have also run the repair approach using as baseline variable mappings generated based on uniform distributions. This case simulates most repair techniques that compute all possible mappings between both programs’ variables (e.g., SEARCHREPAIR [13]).

<table>
<thead>
<tr>
<th>Edges Used</th>
<th>All (1,2,3,4) (0,1,2,3,4) (0,1,3,4) (0,1,2,4) (0,1,2,3) (0,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>96.49% 52.53% 73.76% 95.45% 94.87% 96.06% 94.74%</td>
</tr>
</tbody>
</table>

Table 3 presents the percentage of variable mappings fully correct on the validation set for different sets of edges used. Each type of edge is represented by an index using the mapping: {0: AST; 1: sibling; 2: write; 3: read; 4: chronological}.

Further analysis has shown that programs that are missing expressions (MISS) are more difficult to repair than programs that only contain missing comparison operators (VM) and variable misuse (WCO). This is consistent with prior work [10], which found that programs containing all three types of bugs are the most difficult to repair.

Furthermore, considering all executions, the average number of variable mappings used within 60 seconds is 1.24 variable mappings for the GNN model and 5.6 variable mappings when considering the baseline. The minimum number of mappings generated by both approaches is 1, i.e., both techniques were able to fix at least one incorrect program using the first generated variable mapping. The maximum number of variable mappings generated was 32 (resp. 48) for the GNN (resp. baseline). The maximum number of variable mappings used is high because the repair procedure iterates over all the variable mappings until the program is fixed or the time runs out. Moreover, even if we would only consider using the first variable mapping generated by the GNN model to repair the incorrect programs, we would be able to fix 3377 programs in 60 seconds, corresponding to 81% of the evaluation dataset.

Regarding the time performance of each technique, Figure 3 shows a cactus plot that presents the CPU time spent, in seconds, on repairing each program (y-axis) against the number of repaired programs (x-axis) using different repairing techniques. One can clearly see a gap between the different repair methods’ time performances. For example, in 10 seconds, the baseline can only repair around 1150 programs, VERIFY repairs around 2300, CLARA repairs around 2850 programs while using the GNN’s variable mappings, we can repair around 3350 programs, i.e., around 17% more. We are considering the time the GNN takes to generate the variable mappings and the time spent on the repair procedure. However, the time spent by the GNN to generate one variable mapping is almost insignificant. The average time the GNN takes to produce a variable mapping is 0.025 seconds. The minimum (resp. maximum) time spent by the GNN, considering all the executions is 0.015s (resp. 0.183s).
Table 4: The number of programs repaired by each different repair technique: VERIFIX, CLARA, and our repair approach based on our GNN’s variable mappings. The first row shows the results of repairing the programs using variable mappings generated based on uniform distributions (baseline).

<table>
<thead>
<tr>
<th>Repair Method</th>
<th>WCO Bug</th>
<th>VM Bug</th>
<th>ME Bug</th>
<th>All Bugs</th>
<th>% Failed</th>
<th>% Timeouts (60s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>618</td>
<td>1187</td>
<td>287</td>
<td>2092</td>
<td>0.0%</td>
<td>2074 (49.78%)</td>
</tr>
<tr>
<td>VERIFIX</td>
<td>555</td>
<td>1292</td>
<td>741</td>
<td>2588</td>
<td>1471 (35.31%)</td>
<td>107 (2.57%)</td>
</tr>
<tr>
<td>CLARA</td>
<td>722</td>
<td>1517</td>
<td>764</td>
<td>3003</td>
<td>1153 (27.68%)</td>
<td>10 (0.24%)</td>
</tr>
<tr>
<td>GNN</td>
<td>992</td>
<td>1714</td>
<td>981</td>
<td>3687</td>
<td>0.0%</td>
<td>479 (11.5%)</td>
</tr>
</tbody>
</table>

Figure 3: Cactus plot - The time spent by each method repairing each program of the evaluation dataset, using a timeout of 60 seconds.

6 Related Work

Automated program repair [1, 24, 10, 12, 41] has become crucial to provide feedback to novice programmers by checking their introductory programming assignments (IPAS) submissions using a test suite. In order to repair an incorrect program with a correct reference implementation, CLARA [10] requires a perfect match between both programs’ control flow graphs and a bijective relation between both programs’ variables. Otherwise, CLARA returns a structural mismatch error. VERIFIX [1] aligns the control flow graph (CFG) of an incorrect program with the reference solution’s CFG. Then, using that alignment relation and MAXSMT solving, VERIFIX proposes fixes to the incorrect program. VERIFIX also requires a compatible control flow graph between the incorrect and the correct program. BUGLAB [1] is a Python program repair tool that learns how to detect and fix minor semantic bugs. To train BUGLAB, [1] applied four program mutations and introduced four different bugs to augment their benchmark of Python programs. DEEPBUGS [11] uses rule-based mutations to build a dataset of programs from scratch to train its ML-based program repair tool. Given a program, this tool classifies if the program is buggy or not.

Mapping variables can also be helpful for the task of code adaptation, where the repair framework tries to adapt all the variable names in a pasted snippet of code, copied from another program or a Stack Overflow post to the surrounding preexisting code [25]. ADAP- TIVEPASTE [25] focused on a similar task to variable misuse (VM) repair, it uses a sequence-to-sequence with multi-decoder transformer training to learn programming language semantics to adapt variables in the pasted snippet of code. Recently, several systems were proposed to tackle the VM bug with ML models [3, 13, 40].

These tools classify the variable locations as faulty or correct and then replace the faulty ones through an enumerative prediction of each buggy location [3]. However, none of these methods takes program semantics into account, especially the long-range dependencies of variable usages [25].

7 Conclusions

This paper tackles the highly challenging problem of mapping variables between programs. We propose the usage of graph neural networks (GNNs) to map the set of variables between two programs using our novel graph representation that is based on both programs’ abstract syntax trees. In a dataset of 4166 pairs of incorrect/correct programs, experiments show that our GNN correctly maps 83% of the evaluation dataset. Furthermore, we leverage the variable mappings to perform automatic program repair. While the current state-of-the-art on program repair can only repair about 72% of the evaluation dataset due to structural mismatch errors, our approach, based on variable mappings, is able to fix 88.5%.

In future work, we propose to integrate our variable mappings into other program repair tools to evaluate the impact of using these mappings to repair other types of bugs. Additionally, we will analyze using our mappings to fix an incorrect program using several correct programs.

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References
