InvAASTCluster: On Applying Invariant-Based Program Clustering to Introductory Programming Assignments

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Due to the vast number of students enrolled in Massive Open Online Courses (MOOCs), there has been an increasing number of automated program repair techniques focused on introductory programming assignments (IPAs). Such state-of-the-art techniques use program clustering to take advantage of previous correct student implementations to repair a given new incorrect submission. Usually, these repair techniques use clustering methods since analyzing all available correct student submissions to repair a program is not feasible. The clustering methods use program representations based on several features such as abstract syntax tree (AST), syntax, control flow, and data flow. However, these features are sometimes brittle when representing semantically similar programs.

This paper proposes InvAASTCluster, a novel approach for program clustering that takes advantage of dynamically generated program invariants observed over several program executions to cluster semantically equivalent IPAs. Our main objective is to find a more suitable representation of programs using a combination of the program’s semantics, through its invariants, and its structure, through its anonymized abstract syntax tree. The evaluation of InvAASTCluster shows that the proposed program representation outperforms syntax-based representations when clustering a set of different correct IPAs. Furthermore, we integrate InvAASTCluster into a state-of-the-art clustering-based program repair tool and evaluate it on a set of IPAs. Our results show that InvAASTCluster advances the current state-of-the-art when used by clustering-based program repair tools by repairing a larger number of students’ programs in a shorter amount of time.

CCS Concepts: • Applied computing → Computer-assisted instruction; • Theory of computation → Program semantics; Invariants; Program analysis.

Additional Key Words and Phrases: Program Clustering, Program Invariants, Program Equivalence, Program Repair, Programming Education, MOOCs

1 INTRODUCTION

Nowadays, thousands of students enroll every year in programming-oriented Massive Open Online Courses (MOOCs) [15]. On top of that, due to the current pandemic situation, even small-sized programming courses are being taught online. Providing feedback to novice students in introductory programming assignments (IPAs) in these courses requires substantial effort and time by the faculty. Hence, there is an increasing need for automated semantic program repair frameworks [14, 15, 21, 27, 28, 30, 43, 44] capable of providing automated, comprehensive, and personalized feedback to students in incorrect solutions to programming assignments.

Over the last few years, several program repair tools [15, 19, 32, 41] have exploited a large number of previously enrolled students to obtain diverse correct implementations for each IPA. Given an incorrect student submission, these frameworks use clustering methods to find the most similar correct submission from previous years to provide a minimal set of repairs to the student. Typically, having a similar correct implementation allows computing a smaller set of repairs to fix a given incorrect program rather than always using the set of repairs needed to make the incorrect submission semantically equivalent to a fixed reference solution. However, analyzing all previous correct student submissions for an IPA is not feasible. To tackle this problem, different program

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clustering approaches have been proposed to use in program repair tools which enable focusing only on the representatives of the clusters. CLARA [15] clusters the correct programs based on their dynamic equivalence [29] and control flow, i.e., the order in which program statements, instructions and function calls are executed. SARFGEN [41] computes program representations based on each program’s abstract syntax tree. SEMCLUSTER [32] also uses each program’s control flow. However, SEMCLUSTER uses each program’s data flow which tracks the number of occurrences of consecutive values a variable takes during its lifetime.

The problem of program equivalence, i.e., deciding if two programs are equivalent, is undecidable [6, 34]. On that account, finding an adequate representation for programs that performs well on program clustering is a challenging problem. The above-mentioned program representations used in the field of program repair may be fragile, as we are going to show in Section 2. To address this problem, our work proposes the use of dynamically-generated program invariants to cluster semantically equivalent programs, overcoming some of the identified weaknesses. A program invariant is a condition that must always be true at a given step of the program during its execution (see Section 3.2). Program invariants are usually used to assert some assurances throughout a program (assertions).

This paper proposes to leverage the information of a program’s structure using its abstract syntax tree (AST) together with semantic information provided by its set of invariants. Previous research has been conducted regarding the use of invariants to promote patch diversity (i.e. diversity in the set of possible repairs to a given incorrect program) on search-based program repair [5, 9, 42]. These works use DAIKON [10] to generate invariant sets for each possible patch. DAIKON is a system that infers likely dynamically generated invariants observed over several program executions. Therefore, these invariants are dependent on the program executions. Nevertheless, previous work [5] showed promising results in using invariants to semantically cluster patches to provide the user with a semantic reason for a set of similar patches.

This paper presents a novel approach for clustering introductory programming assignments (IPAs) leveraging their sets of invariants. Our approach for clustering IPAs also takes into account each program’s code and anonymized abstract syntax tree (AAST) (see Section 4.2). The main contribution of this work is a vector representation of programs based on the programs’ invariants and their AASTs, bringing together the programs’ semantics and syntactic features. The proposed clustering technique has been implemented in a framework InvAASTCluster. This tool has been designed as an independent clustering tool. Therefore, it can be used to help evaluate students’ submissions for IPAs by clustering semantically equivalent solutions for programming exercises, although InvAASTCluster can also be easily integrated into any clustering-based program repair tool for IPAs. Furthermore, InvAASTCluster can even be used in a plagiarism detection tool, like Moss [35].

Figure 1 shows the generic idea of clustering-based program repair frameworks [15, 32, 41]. These frameworks [15, 32, 41] receive an incorrect student submission, a test suite, and a collection of \( N \) correct student submissions for the same IPA. For scalability concerns, these frameworks eliminate, through clustering techniques, semantically equivalent solutions, i.e., dynamically equivalent correct programs given the provided input-output test suite. Those clustering approaches try to aggregate the set of \( N \) correct solutions into \( K \) semantically different clusters (\( N \gg K \)). Finally, the repair tool uses these \( K \) clusters’ representatives to repair the provided incorrect student submission. As Figure 1 shows, InvAASTCluster can be used as the clustering technique of those clustering-based program repair tools. However, some program repair tools [2, 23] use a single reference implementation provided by the lecturer to repair a student’s program. These tools usually are only able to use one correct implementation to repair each program. Therefore, given an incorrect submission, InvAASTCluster was designed to be also capable of finding on a set
of correct student submissions which submission is the closest correct solution to the incorrect program, i.e., a specific reference implementation for each incorrect submission, that may require fewer changes to fix the program.

We evaluate InvAASTCluster on a set of real-world student programs developed during a university introductory programming course. Experimental results show that the proposed invariant-based representation improves upon syntax-based representations when performing program clustering. We integrate InvAASTCluster into Clara, a clustering-based program repair tool, in order to compare our clustering technique against Clara’s clustering method, which is the current publicly available state-of-the-art method for clustering IPAs.

To summarize, this paper makes the following contributions:

• We propose a novel and efficient approach for clustering submissions for introductory programming assignments (IPAs) based on the submissions’ sets of invariants and AASTs representations.
• We present a study showing the results of using our program clustering tool, InvAASTCluster, on a set of 1620 real-world IPAs correct submissions to show the effectiveness of invariant-based program clustering.
• We compare InvAASTCluster with the clustering method used by the currently available state-of-the-art program repair tools. Experimental results show that using our technique for program clustering or finding the closest correct solution, InvAASTCluster outperforms current state-of-the-art clustering methods.
• The InvAASTCluster framework is publicly available on GitHub at https://github.com/pmorvalho/InvAASTCluster.

The structure of the remainder of this paper is as follows. First, Section 2 illustrates the strengths of using invariants for program representation. Section 3 presents important concepts used throughout this manuscript and describes how to gather and represent sets of program invariants. Section 4 discusses several program representations, including a new invariant-based program representation. Section 5 discusses the implementation of InvAASTCluster. Section 6 presents the experimental evaluation that supports our claim that invariant-based program representations are beneficial to cluster semantically programming assignments. Finally, Section 7 presents the related work, and the paper concludes in Section 8.

2 MOTIVATION

Current program representations for repairing students’ programming assignments leverage certain program features, such as code syntax [16], abstract syntax tree [41], control flow [15] and data
flow [32], to encode each program into a vector representation. However, all of these features have some weaknesses when we want to cluster programs based on their semantics.

Example 1. Consider the following two programs written in C:

Both programs in Example 1 compute the sum of all the natural numbers from 1 to a given number \( n \) i.e. \( \sum_{i=1}^{n} i \). Observe that the program on the left uses a while-loop that iterates over the natural numbers from 0 to \( n \). However, the program on the right uses a for-loop that iterates from \( n \) to 0 in decreasing order. Nevertheless, if we build a program representation using the programs’ syntax or abstract syntax trees, both programs will have very different representations. In terms of syntax, the names of the used variables (e.g. \( i, j, s, \) sum) and structures (e.g. while, for) are different. Additionally, in terms of data flow and dynamic equivalence, both programs are also different since, for example, the values assigned to the variable \( i \) go from 0 to \( n \) in the first program while in the other the variable \( j \) is assigned the same values but in decreasing order.

Consider that the variable \( n \) is always assigned to a natural number, \( n > 0 \). In the first program, if a dynamic invariant detector (e.g. DAIKON [10]) is used, the following set of invariants is observed:

- In the first program, at each iteration of the while-loop: \( n > 0; \) \( \sum \geq 0; \) \( 0 \leq i \leq n \).
- In the second program, at each iteration of the for-loop: \( n > 0; \) \( s \geq 0; \) \( 0 \leq j \leq n \).

Therefore, after renaming some variables (\( \text{sum} \rightarrow s; i \rightarrow j \)), these two sets of invariants would be considered equivalent. Hence, using sets of invariants allows finding semantically equivalent programs that can differ in their syntax and/or in their data flow.

Hence, the idea of this paper is to improve the semantic representation of IPAs using their sets of invariants. These invariants are dynamically detected by DAIKON [10] over several program executions using a predefined set of test cases for each programming assignment. In addition to the set of invariants, which provides semantic information about a program, the idea is also to leverage the information of a program’s anonymized abstract syntax tree (AAST), i.e. an AST after removing all the variables’ names.

3 SYNTAX TREES AND INVARIANTS

This section provides some background on syntax trees and program invariants that will be used throughout this paper.

3.1 Definitions

Definition 3.1 (Context-free Grammar (CFG)). A context-free grammar \( \mathcal{G} \) is a 4-tuple \((V, \Sigma, R, S)\), where \( V \) is the set of non-terminals symbols, \( \Sigma \) is the set of terminal symbols, \( R \) is the set of rules and \( S \) is the start symbol. A CFG describes all the strings permitted in a certain formal language [18].

Definition 3.2 (Domain-Specific Language (DSL)). A Domain-specific Language (DSL) is a tuple \((\mathcal{G}, \text{Ops})\), where \( \mathcal{G} \) is a context-free grammar \((\mathcal{G} = (V, \Sigma, R, S))\) and \( \text{Ops} \) is the semantics of
Definition 3.3 (Abstract Syntax Tree (AST)). An abstract syntax tree (AST) is a syntax tree in which each node represents an operation, and the children of the node represent the arguments of the operation for a given programming language described by a Context-free Grammar [18]. An AST depicts a program’s grammatical structure [3].

Figure 2a presents a small example of the AST representation for the variable declaration \texttt{int \ i}.DSL operators. The CFG \mathcal{G} has the rules to generate all the programs in the DSL. The semantics of DSL operators is necessary to analyze conflicts and make deductions.

Definition 3.4 (Anonymized Abstract Syntax Tree (AAST)). An anonymized abstract syntax tree (AAST) is an AST in which nodes that have identifiers are anonymized, i.e., a node’s identifier (name of a function or variable) is replaced by a special token (ID).

Figure 2b shows the AAST representation for the same declaration presented previously, \texttt{int \ i}.

Definition 3.5 (Bag of Words (BoW)). A Bag of Words (BoW) representation [17] is a vector representation where a tokenized sentence is represented as a bag of its words in a vector. The vector representation contains information on the number of times each token in the language appears in the sentence. Note that this model does not take into consideration the language’s grammar and even word order. The tokenization step divides a string into n-grams, which are sub-sequences of the original string of n items.

The following example presents a small illustration of a vector representation of a phrase using a BoW model.

Example 2. Let \( V \) be a language that contains only 5 symbols in its vocabulary i.e., \( \Sigma_V = \{a, e, i, o, u\} \). Let \( B_V \) be a bag of words model computed using the following sentences written in \( V \): \{"a a", "e i", "a e i o u", "o i"\}.

Given the phrase \( p = "a i a u\)" , the vector representation of \( p \) is, \( B_V(p) = [0.5, 0.0, 0.25,-0.0, 0.25] \). The size of \( B_V(p) \) is 5 since 5 is the size of \( \Sigma_V \). For each entry \( s \) of \( B_V(p) \), \( B_V(p)[s] \) corresponds to the percentage of \( p \) that is equal to \( s \). For example, the symbol \( a \) appears twice in a four-symbol phrase. Hence \( B_V(p)["a"] = 0.5 \).

3.2 Program Invariants

Program invariants are conditions that must always be true at a given point during a program’s execution. Dynamically generated program invariants are likely invariants observed during several program executions for a given program. The dynamically generated set of program invariants provides information about a program’s behavior, i.e. its semantics. If two programs share the same set of program invariants, they are likely semantically equivalent. Hence, an invariant-based representation of programs should allow to find out which student submissions in a given programming assignment have the same or similar behavior.
To compare two sets of program invariants, a relation between the variables in both sets is required. We propose to rename all the variables in a program based on the variables’ type and usage. All the variables are renamed the first time they are assigned to some value in a program. The variable’s new name is a concatenation between its type and a counter for how many variables have already been renamed in the program. With this technique of variable renaming, two programs’ sets of invariants can be easily compared. This method is very simple and fragile, although IPAs are usually relatively small and simple imperative programs. Therefore, this naive approach should work for IPAs.

Example 3. Consider again the programs presented in Example 1, after renaming all the variables based on their usage, the following mapping of variables for the first program is obtained \{\text{sum} \rightarrow \text{int}_0; \ n \rightarrow \text{int}_1; \ i \rightarrow \text{int}_2\}. Regarding the second program the mapping is \{\text{s} \rightarrow \text{int}_0; \ n \rightarrow \text{int}_1; \ j \rightarrow \text{int}_2\}. The two programs after renaming are:

```
1 int int1, int0 = 0, int2;
2 scanf("%d", &int1);
3 int2 = 0;
4 while(int2 < int1){
5    int2++;
6    int0 = int0 + int2;
7 }
8 printf("%d\n",int0);
```

Hence, the set of invariants of both cycles (for and while) would be the same: \{\text{int}_1 > 0; \ \text{int}_0 \geq 0; \ 0 \leq \text{int}_2 \leq \text{int}_1\}.

In this work, we use Daikon [10] to compute dynamically-generated likely invariants observed over several program executions for each student submission using a set of predefined input-output tests for each programming assignment. First, the method for renaming variables is applied to all the students’ submissions. To use Daikon on small imperative C programs, one must inject empty functions into each scope and pass the scope’s variables as parameters. Afterward, Daikon is executed using all the input tests for each programming assignment. The dynamically-generated invariants produced by Daikon are saved for each program’s structure/scope (e.g. if, cycle, block). We don’t specifically ask Daikon to generate any type of invariant. The only type of invariants we turned off is the “OneOf” invariants (e.g. “x is OneOf \{1,2\}”) that may cause overfitting to the test suite.

4 PROGRAM REPRESENTATIONS

In this work, each program is represented as a feature vector. In particular, we propose to use a bag of words (BoW) model (see Definition 3.5). Using BoW models, we generate vector representations for each student submission based on several features. These features may include the Abstract Syntax Tree (AST), set of invariants, or even the program code. It is also possible to combine several of these features. Next, all the vector representations used in this work are described.

4.1 Syntax Vectors

The syntax vector program representation is the simplest to compute since it is based solely on the program syntax (code). In the interest of comparing the syntax of programs independently of the variables’ names, first, all the programming solutions are renamed using the method described in
Section 3.2. Next, all the student submissions are tokenized, and a vocabulary with all the available tokens is obtained. Then, vectors for each student submission are created, where the $i^{th}$ entry is the number of times the $i^{th}$ word of the vocabulary that appears in the program. Finally, the numbers of occurrences in these vectors are normalized.

4.2 Anonymized Abstract Syntax Tree Vectors

An alternative representation is to compute a bag of words using the strings of the abstract syntax trees (AST) of all submissions for a given programming assignment. This representation has already been used in program clustering [20, 41]. However, we represent each AST as a string and remove all names of variables and functions, keeping only their respective types in the AST. Thus, for each submission, we have an anonymized abstract syntax tree (AAST) (see Definition 3.4). With these AASTs, we keep the information about a program’s structure, ignoring the name of its variables. The information about a program’s structure is kept since an AAST contains all the non-terminal symbols of a language’s grammar. Next, a vocabulary is built with the tokens present in all submissions and a normalized vector representation for each AAST is computed.

4.3 Invariant Vectors

Another approach is to use an invariant-based vector representation. In this case, we apply the bag of words model to the set of invariants of the programs. We gather all program invariants as described in Section 3.2. Previous work on the use of invariants to detect semantic similarity between possible patches to a program [5] showed that using string distance measure between invariant sets had similar results and was more efficient than computing the logical similarity between their corresponding sets of program invariants. Therefore, we represent our invariants in the form of strings. However, instead of using a string distance measure between invariant sets (e.g. Levenshtein edit distance [22]), we create a bag of words model with those sets of program invariants.

4.4 Combination of Program Features

Finally, observe that these vector representations (Syntax, AAST, Invariants) can be combined, thus taking advantage of using several types of features. For example, we use in our work a bag of words using the program’s AST and the sets of invariants. In this case, first, we build two BoW representations independently, one based on AASTs and another one based on invariants. Then, we concatenate, for each submission, the submission’s vector representations using the two BoWs, achieving a vector representation based on the program’s AAST and set of invariants. The program syntax was not included in this last representation since the BoW based on syntax has a large vocabulary that generates vectors too sparse.

5 IMPLEMENTATION

This section presents the implementation of our program clustering technique. We implemented the proposed approach in the tool InvAASTCluster (Invariants and AAST Program Clustering). InvAASTCluster is publicly available on GitHub at https://github.com/pmorvalho/InvAASTCluster. Figure 3 shows the overall architecture of the tool. Given a set of $N$ correct submissions and a test suite, InvAASTCluster computes $K$ clusters of programs ($N \geq K$) and returns the set of $K$ clusters’ representatives, i.e. the set of correct programs that are in the center of each one of the $K$ clusters. InvAASTCluster is divided into six main modules: variable renamer, invariants detector, AASTs processor, bag of words maker, clustering procedure and the selection of each cluster representative.
Variable Renamer. In this module, InvAASTCluster renames all variables of each one of the $N$ given correct submissions. All variables are renamed based on their usage in each program, as explained in Section 3.2. Hence, InvAASTCluster uses `pycparser`\(^1\) to find all variables in a program. Then, when a variable is first used in the program (e.g. assignment) that variable receives a new name taking into consideration the variable’s type.

Invariants Detector. InvAASTCluster uses Daikon [10] to compute dynamically-generated invariants for a given test suite. After all the variables have been renamed, this module produces a set of invariants for each program’s scope using the provided test suite. All these sets of invariants are then sent to the BoW maker module.

AAST Processor. In this step, InvAASTCluster also uses `pycparser` to compute a program’s abstract syntax tree (AST). Additionally, InvAASTCluster removes from the AST all the variables’ and functions’ identifiers to transform the program’s AST into an anonymized abstract syntax tree (AAST), conserving only the program’s structure.

Bag of Words (BoW) Maker. This module receives three sets as input: (1) the set of correct program submissions with all their variables renamed from the Variable Renamer module; (2) all the program’s AASTs from the AAST processor and (3) the set of the programs’ dynamically-generated invariants. The BoW Maker computes the bag of words (BoW) model that is going to be used to generate vector representations for each program. Depending on this module’s parameterization, the BoW maker can compute four different bags of words: (1) based on the programs’ code (syntax), (2) based on the programs’ AASTs (structure), (3) using the set of programs’ invariants (semantics) and (4) joining the programs’ AASTs and their sets of invariants (structure + semantics). To compute these BoW models, InvAASTCluster uses scikit-learn package, `feature_extraction`\(^2\).

InvAASTCluster tokenizes the input strings, into tokens of size $n$ ($n$-grams), to build a vocabulary with all the submissions’ information, i.e. invariants, syntax, or AASTs. In our case, we define $n = 3$ (3-grams) for this parameter of the BoW maker. Afterward, once a vocabulary has been collected, InvAASTCluster computes for each program a vector representation by counting

\(^1\)https://github.com/eliben/pycparser
\(^2\)sklearn.feature_extraction.text.TfidfVectorizer
the number of times each token appears in the program’s information string (invariants, syntax, or AASTs) and normalizing the vector by the length of the BoW’s vocabulary.

Clustering. The number of desired clusters $K$ is also a parameter of InvAASTCluster, although by default InvAASTCluster searches for a number of clusters that corresponds to 10% of $N$. The BoW maker module passes to the clustering procedure the set of vector representations for each one of the $N$ correct submissions. Then, InvAASTCluster uses the $KMeans$ algorithm to cluster these submissions into $K$ different clusters. The $KMeans$ algorithm receives as a parameter the number of clusters it should return ($K$). The KMeans algorithm divides the set of observations, in our case students’ programs, into $K$ clusters where each program is assigned to the cluster with the nearest mean [37]. InvAASTCluster uses KMeans however other clustering algorithms can be applied.

Clusters’ representatives selection. In this last module, InvAASTCluster chooses a program representative for each cluster, i.e. for each one of the $K$ clusters, InvAASTCluster computes which is the program that is closest to the cluster’s center. To compute these distances InvAASTCluster calculates the Euclidean distance between the programs’ vector representation of each cluster. Afterward, InvAASTCluster returns a set of $K$ clusters’ representatives.

Easy upgradability. InvAASTCluster was designed with modularity in mind. On that account, one can easily remove, add or modify any module of InvAASTCluster. For example, one can choose to use other models instead of the bag of words model only needing to replace that specific procedure.

Several program repair tools [2, 19, 23] only accept one correct program to act as a reference implementation for repairing a given incorrect program. Hence, these frameworks cannot take advantage of a vast number of semantically different student correct submissions. In order to integrate InvAASTCluster in these frameworks, we developed an additional module that finds the closest correct program representative to an incorrect program.

Closest correct program finder. The overall idea of this additional module is presented in Figure 4. Given a student’s incorrect submission, InvAASTCluster finds which of the $K$ clusters’ representatives, returned by InvAASTCluster’s selection module, is the closest program to the
Table 1. Description of our dataset of IPAs.

| Labs  | #IPAs | #Correct Submissions | #Incorrect Submissions | #IPAs (CLARA) | #Correct Submissions (CLARA) |
|-------|-------|----------------------|------------------------|---------------|-------------------------------|
| Lab02 | 10    | 789                  | 118                    | 10            | 738                           |
| Lab03 | 7     | 363                  | 35                     | 5             | 244                           |
| Lab04 | 8     | 468                  | 43                     | 5             | 159                           |
| Total | 25    | 1620                 | 196                    | 20            | 1141                          |

incorrect submission. This is done by identifying the smallest Euclidean distance between the vector representation of each one of the clusters’ representatives and the incorrect submission. Hence, we can identify one correct program that is most likely the reference implementation to use for repairing a specific student’s program. In the example of Figure 4, InvAASTCluster would return only the $C^{th}$ program to the repair framework since it is the closest program to the incorrect submission.

6 EXPERIMENTS

The experimental results presented in this section aim to support our claims that the proposed novel program representation based on a program’s AAST and its set of program invariants help: (1) to efficiently cluster semantically equivalent small imperative programs submitted in IPAs, and (2) to repair faster and significantly more IPAs’ incorrect submissions in current state-of-the-art clustering-based program repair tools, such as CLARA [15].

The goal of our experiments was to answer the following research questions:

Q1. How does invariant-based program clustering compare against AAST and syntax-based clustering on a set of correct submissions?
Q2. How does InvAASTCluster compare against CLARA’s clustering technique in terms of the number of clusters generated, the time spent, and the number of changes needed to fix IPAs?
Q3. Does CLARA repair more programs using InvAASTCluster’s closest correct submission or its set of KMeans clusters’ representatives?
Q4. Are program invariants a helpful source of information to use on program representations of incorrect programs?

To answer these research questions, we evaluate InvAASTCluster on two different use cases: (1) clustering IPAs, and (2) repairing IPAs. For this evaluation, we have gathered a set of IPAs, described in Section 6.1, developed during an introductory programming university course in C language. Section 6.2 presents the first use case where we perform clustering on the students’ program set and evaluate its accuracy on different program representations. Afterward, Section 6.3 shows the second use case where we integrate our program representations into a state-of-the-art program repair tool, CLARA [15], to evaluate if our clustering technique is able to outperform CLARA’s clustering method, which is the only current publicly available state-of-the-art clustering method for repairing IPAs. All of the experiments were conducted on an Intel(R) Xeon(R) Silver computer with 4210R CPUs @ 2.40GHz, using a memory limit of 64GB.

6.1 Introductory Programming Assignments (IPAs) Dataset

To evaluate the program representations described in Section 4, we gathered a set of student programs developed during an introductory programming course in C language were collected over three distinct practical classes at Instituto Superior Técnico for 25 different IPAs. Since this work
focuses only on program semantics, only submissions that compile without any error were selected. The set of submissions was split into two sets: correct submissions and incorrect submissions. The students’ submissions that satisfied a set of input-output test cases for each IPA were considered correct and selected as benchmark instances. The submissions that failed at least one input-output test were considered incorrect. Table 1 presents the number of submissions gathered. For 25 different programming exercises, this dataset contains 1620 different correct and 196 incorrect submissions. CLARA’s clustering method does not support all the features present in the correct submissions collected. Hence, as shown in Table 1, after removing the set of exercises and correct programs that CLARA does not support, we achieved a final set of 1141 correct submissions for 20 IPAs. This dataset of introductory programming exercises, C-Pack-IPAs, is publicly available at https://github.com/pmorvalho/C-Pack-IPAs and can be used by other IPAs repair/clustering frameworks. In this git repository, the interested reader can find all the information about description and the input-output tests used to evaluate each IPA [31].

6.2 Use Case 1: Clustering IPAs

A study was performed to evaluate different program representations by applying program clustering to the set of correct programs described in Table 1. The main idea of this experiment was to
evaluate if program invariants help identify different IPAs’ submissions. Hence, InvAASTCluster was used to cluster the 1620 correct submissions into 25 distinct clusters since our dataset has 25 different programming exercises. Other works [32] that perform program clustering on IPAs perform an equivalent study on clustering submissions for different assignments. The main reason to cluster submissions to different IPAs is that we know the ground truth label for each program since we know for which specific IPA the students submit their assignments. Otherwise, we had to manually choose semantically different implementations for the same IPA and assign labels which might be subjective.

InvAASTCluster, as explained in Section 5, starts by renaming all the variables in the student submissions. Then uses Daikon [10] to collect the student submissions’ dynamically generated invariants sets as described in Section 3.2. Lastly, it uses the python library, pycparser³, to compute all the anonymized abstract syntax trees (AAST) (see Section 4.2). Using all these program features, we computed four different bags of words models. One model for each program representation (syntax, AAST, and invariants) and one representation using a combination of a program’s AAST and its invariants set. The program syntax is not included in this last representation since the bag of words based on program syntax has a large vocabulary that generates too sparse vectors.

The following clustering algorithms available in scikit-learn⁴ were applied to each program representation: KMeans (see Section 5), MiniBatch KMeans, BIRCH and Gaussian Mixture. We focus the discussion on the KMeans results, the clustering algorithm that achieved the best results (see Table 2). Since this dataset has 25 different programming exercises, the ground truth has 25 different clusters. Each student program is a submission to a specific programming exercise (label) that we know. On that account, the cluster accuracy metric can be used to evaluate the obtained clusters. With this metric, each cluster is assigned to the label (exercise), which is most frequent in the cluster. Afterward, the accuracy of this assignment is measured by counting the number of correctly assigned student submissions and dividing by the number of total submissions. This metric is also known as purity [36].

Figure 5 presents the results of applying the KMeans model to each one of the four program representations being analyzed. To present graphically these results, we used a method for visualizing high-dimensional data in a 2−dimension map, called t-SNE [40]. Each subfigure corresponds to a different type of representation. The left-side of each subfigure shows the clustering results and the value of the cluster accuracy (right-bottom corner). The right side presents the real clusters of each programming exercise, i.e. the ground truth represented using each program representation. Figure 5a shows the results after clustering all the student submissions using a syntax representation, which resulted in a cluster accuracy of almost 59%. The AAST representation achieved a cluster accuracy of 78.7% as presented in Figure 5b. Regarding the use of program invariants, Figure 5c and Table 2 support the idea that program invariants help to improve program clustering since this representation obtained a cluster accuracy of 79.3% using KMeans. Furthermore, Table 2 shows that for all clustering algorithms, this representation based on AAST and invariants achieved the best cluster accuracy. Lastly, Figure 5d presents the representation that uses the combination AASTs and invariants sets, which also shows an improvement compared to the invariant-based representation. This representation outperforms all the other representations with an accuracy of 83.4%. Another advantage of this representation is that it is the best one separating all the students’ submissions in different regions of the space, i.e. the majority of the clusters are visibly separated from each other.

³https://github.com/eliben/pycparser
⁴https://scikit-learn.org/stable/modules/clustering.html
Table 3. Description of ITSP [43] dataset. Correct programs that our approach and CLARA do not support were removed.

| ITSP Dataset | #IPAs | #Correct Submissions | #Incorrect Submissions |
|--------------|-------|----------------------|-----------------------|
| Lab3         | 4     | 45                   | 63                    |
| Lab4         | 6     | 74                   | 75                    |
| Lab5         | 7     | 64                   | 62                    |
| Lab6         | 6     | 19                   | 24                    |
| Total        | 23    | 202                  | 224                   |

Table 4. For each clustering method, this table presents the number of submissions repaired, the number of structural mismatch errors and timeouts.

| Clustering Method                  | #Submissions Repaired | #Structural Mismatch | #Timeouts (600s) |
|------------------------------------|-----------------------|----------------------|------------------|
| 1 CLARA                            | 229 (71.79%)          | 24 (7.52%)           | 66 (20.69%)      |
| 2 KMEANS - Invs                     | 263 (82.45%)          | 38 (11.91%)          | 18 (5.64%)       |
| 3 KMEANS - Syntax                  | 268 (84.01%)          | 35 (10.97%)          | 16 (5.02%)       |
| 4 KMEANS - AAST                    | 270 (84.64%)          | 31 (9.72%)           | 18 (5.64%)       |
| 5 KMEANS - AAST + Invs             | 271 (84.95%)          | 32 (10.03%)          | 16 (5.02%)       |
| 6 Closest Program (KMEANS) - AAST + Invs | 269 (84.33%)   | 34 (10.66%)          | 16 (5.02%)       |

6.3 Use Case 2: Repairing IPAs

In this section, we present the results of integrating INVAASTCLUSTER as the clustering approach for CLARA [15], a publicly available state-of-the-art clustering-based program repair tool. Since our set of IPAs, described in Table 1, has a small percentage of incorrect submissions, only 196, for this evaluation, we have also considered the ITSP dataset [43]. The ITSP dataset has been used by other automated software repair tools [2, 43] that use only one reference implementation. This dataset is also a collection of C programs although it is well balanced, i.e., the number of correct submissions is closer to the number of incorrect submissions in this dataset. Table 3 presents the number of programs in the ITSP dataset after we removed the programs that CLARA and our variable renamer module do not support. Thus, overall we have a total of 420 incorrect submissions (196 from our dataset plus 224 from the ITSP dataset) and 1343 correct submissions (1141 from our dataset plus 202 from the ITSP dataset) for 43 different IPAs (20 from our dataset plus 23 from the ITSP dataset). To fully evaluate our clustering technique for repairing IPAs, we are going to compare INVAASTCLUSTER’s results against CLARA’s in terms of: (1) the number of student submissions repaired; (2) the number of clusters produced by each clustering approach for each IPA; (3) the quality of the repairs proposed and (4) the time spent to repair each incorrect submission.

6.3.1 CLARA’s Clustering Approach. CLARA puts two programs into the same cluster if they have the same control flow structure and if there exists a mapping between their variables [8]. CLARA requires a perfect match between the two programs’ control flow graphs (i.e. branches, loops, functions) and a bijective relation between both programs’ variables. Otherwise, CLARA returns a structural mismatch error, and those programs are not clustered together. For each computed
cluster, CLARA keeps all the programs’ information (e.g. expressions, variables) that belong to that cluster.

**CLARA’s Repairing Process.** To repair a given incorrect program, CLARA receives one or a set of correct programs. This set of programs can correspond to clusters’ representatives produced by CLARA. If so, then CLARA should also receive all the information about the programs that are in each cluster to help with the repair process. During CLARA’s repair process, if none of the correct programs provided has an exact match with the incorrect submission’s control flow, then CLARA is not able to repair the program and returns a **Structural Mismatch** error. Otherwise, CLARA gathers the set of repairs using each correct program and returns the minimal one.

### 6.3.2 Results.
This experiment compares INVAASTCluster against CLARA’s clustering technique. Different procedures for program clustering using INVAASTCluster (see Table 4) are evaluated:

- **KMEANS - BoW**: Uses KMEANS and four different BoW based on AAST, syntax and invariants (lines 2–5 in Table 4);
- **Closest Program (KMEANS) - AAST + Invs**: Uses the closest program (see Section 5) using the AAST + Invs BoW, from a set of clusters’ representatives using KMEANS (line 6);

Table 4 presents the overall repair evaluation on 319 incorrect submissions since CLARA’s repair algorithm does not support the C implementation of 101 incorrect submissions (24.05% of the instances). Entries in bold correspond to the highest number of submissions repaired, the lowest
number of errors of structural mismatch, or the lowest number of executions that did not repair a program using a timeout of 10 minutes (600s). CLARA’s clustering technique (line 1, Table 4) can only repair 229 (around 72%) of the incorrect submissions and shows the largest percentage of instances that were not repaired due to timeout (20.69%). InvAASTCluster using KMEANS and the BoW based on AAST and Invariants achieved the highest score, repairing 84.95% of the supported incorrect submissions. The bag of words based only on invariants has the highest percentage of structural mismatch (11.91%), which may be explained by CLARA’s inability to use a program with a different control flow in the repair process. Using only invariants on a vector representation helps clustering programs with similar semantics, although it does not take into account the programs’ structure (control flow). Hence, a higher rate of structural mismatch is observed. Since the BoW based on AASTs and invariants achieved the best results either in the program clustering experiment (see Section 6.2) as when repairing submissions using InvAASTCluster with KMEANS’ clusters (lines 2-5 in Table 4), we opted to only use the BoW based on AAST and invariants when finding the closest correct program (line 6, Table 4). Regarding the use of just one correct solution to fix an incorrect submission, the Closest Program (KMEANS) approach did not achieve better results than using the set of clusters’ representatives.

We have also analyzed this technique using all submissions, i.e., use the closest program among all submissions (no clustering step). This approach, the Closest Program (All Submissions), was able to repair 86.5% of the submissions. The number of timeouts in this approach and using KMEANS was similar. Once again, this high rate of repaired programs (86.5%) may be explained by CLARA’s strict requirements for both programs, the program being repaired and the correct program used by the repair process, to have the same control flow. Therefore, when InvAASTCluster finds the closest program among all submissions instead of using clusters, InvAASTCluster has a collection of programs’ structures more diverse. Consequentially, the Closest Program (All Submissions) approach also achieved the lowest score of structural mismatch errors (only 9.4%). Although we would like to draw the reader’s attention to the difference between the number of submissions repaired using KMEANS (85%) or using the closest correct program (86.5%), which is less than 2%. Furthermore, the computation to find the closest correct program among all correct submissions can only be done online since it requires the student’s incorrect program. On the other hand, the computation of the KMEANS clusters can be done offline since it only requires past students’ correct submissions. In this evaluation, this is not a concern since each IPA has at most a hundred correct submissions. However, in a large-scale MOOC with thousands of correct submissions per exercise, the process of finding the closest correct program among all of the submissions may become impractical. To conclude, although the closest correct program with all submissions was able to repair slightly more programs in this study, in practical large-scale scenarios, it is not feasible to compute in a short period of time. However, KMEANS’ clusters do not suffer this limitation since clusters can be computed offline.

6.3.3 Number of Clusters. Figure 6 shows several cactus plots. The plot in Figure 6a presents the number of clusters used by each clustering method (y-axis) for each IPA (x-axis). This plot also shows the number of correct submissions per IPA. The legend in Figure 6a is sorted in decreasing order of the number of clusters used. One can see that CLARA generates an enormous quantity of clusters, almost half of the correct submissions of each IPA. This large number of clusters is explained by CLARA’s strict clustering method, that does not allow two programs to be in the same cluster if there is not an exact match between both programs’ control flows. InvAASTCluster using the KMEANS clustering algorithm produces K, which in this experiment was always 10% of the number of correct submissions of each exercise. The technique that uses the closest correct program has only a single cluster which is the closest correct program. This evaluation of the
number of clusters used by each approach allows us to observe that CLARA produces a large number of clusters, resulting in a detriment of performance. However, our approach can generate fewer clusters resulting in a more effective repairing process.

6.3.4 Quality of repairs. To compare the quality of repairs obtained using CLARA’s clusters against INVAASTCLUSTER’s clustering method, we analyze the number of changes needed to repair a given incorrect submission, i.e. the set of fixes a program needs to become compliant with the test suite. Figure 6b shows a scatter plot comparing CLARA’s clusters against INVAASTCLUSTER using the BoW based on AAST and Invariants. Each point in the scatter plot represents an incorrect student submission where the x-value (resp. y-value) is the number of changes required to fix a program using INVAASTCLUSTER’s (resp. CLARA’s) clusters. This plot shows that for the programs that both approaches can repair, CLARA usually requires fewer changes to fix the program. Once again, this may be explained by CLARA’s strict requirements for both programs (incorrect and correct programs) used by the repair process to have the same control flow. When CLARA uses the set of KMeans’ clusters, if the best cluster’s representative, according to our program representation, does not have the same control flow, then CLARA cannot use this program in the repair process. Hence, CLARA uses another cluster’s representative, one that has the same control flow although may not have the same semantics. This translates into more changes to fix the incorrect submission. Since CLARA’s clustering technique produces significantly more clusters (almost 50% of the correct submissions), when CLARA uses its own clusters has a more diverse number of programs which means more control flow options, although that is also the reason why CLARA has the lowest repair score in Table 4. Perhaps if we would integrate INVAASTCLUSTER into another repair framework more permissive in terms of control flow, it would result in fewer changes required to fix each incorrect submission.

6.3.5 CPU time. Figure 6c shows the CPU time spent on repairing programs using different clustering techniques. The legend in this plot is sorted in decreasing order of the number of submissions repaired with a timeout of 600s. One can clearly see a gap between CLARA’s time performance and INVAASTCLUSTER’s (considering any clustering approach). There are two main reasons for this gap. First, CLARA produces a significantly larger number of clusters compared to INVAASTCLUSTER (see Figure 6a). Consequently, CLARA must compute a set of repairs for each cluster’s representative. Thus, a bigger number of clusters implies more time spent in the repair process. As for the second reason, as explained in Section 6.3.1, CLARA keeps the information (e.g. variables, expressions) of all the programs that belong to the cluster. During the repair algorithm, CLARA uses all this information to repair a given submission. Hence, the use of all this information translates into more time spent on the repair process. The main goal of educational program repair frameworks is to provide real-time feedback to students on how they should repair their submissions. In this evaluation, we used a timeout of 10 minutes. However, a student expects a faster result. Therefore, Figure 6d shows another cactus plot that shows the time performance of the clustering approaches, although with a timeout of 10 seconds. One can see that after 10 seconds, CLARA using its own clusters, is only able to repair around 150 submissions (47%). On the other hand, using INVAASTCLUSTER, CLARA can repair around 200 submissions (63%).

6.3.6 Program invariants of incorrect submissions. We have also tried the method Closest Program (KMEANS) with INVAASTCLUSTER not taking into account incorrect submissions’ invariants to check if incorrect submissions’ sets of invariants had a negative impact on program representations. First, INVAASTCLUSTER clustered all the correct programs considering their AASTs and their sets of invariants. Secondly, to find the closest correct program to an incorrect submission INVAASTCLUSTER used only the AAST BoW. However, this combined approach of clustering with one BoW
(AASTs + invariants) and calculating the programs’ distances with another (AASTs only) was only able to repair 269 submissions (84%). Thus, according to this experiment, incorrect submissions’ sets of program invariants do not cause negative effects on program representations.

To summarize, in Section 6.2 we used InvAASTCluster to cluster different IPAs correct students’ submissions. The obtained results support that this work’s novel program representation based on a program’s AAST and invariants has better performance when compared to representations solely based on a program’s code, AST or set of program invariants. Furthermore, in Section 6.3, we integrated InvAASTCluster into CLARA to evaluate our tool for repairing IPAs. This study shows that InvAASTCluster significantly increases the current state-of-the-art clustering technique’s performance by allowing CLARA to repair more student submissions and notably faster.

6.4 Threats to Validity

This work relies on Daikon to compute dynamically-generated likely invariants. Using another tool to detect likely invariants may produce different results. Dynamically-generated likely invariants depend highly on the test suite used for each programming exercise. Therefore, using a different set of input-output tests may produce different sets of program invariants for each student submission. For this work’s evaluation, only C programs were used. However, our clustering methods are general and can be applied to other programming languages. To apply InvAASTCluster on other programming languages requires the replacement of: the variable renaming module with one that supports the new language and InvAASTCluster’s invariants detector module for another program invariant detector that works for the desired language. A different repair tool may produce different results since the repair process may be different. For example, another tool may support C features that CLARA currently does not support or the opposite. Only small imperative programs, usually found in IPAs, were used to evaluate InvAASTCluster. The use of InvAASTCluster on more complex programs is left for future work.

7 RELATED WORK

Program clustering has also been used to find different semantic solutions for a given programming exercise [7, 12, 13]. PaCon [12] clusters programming assignments based on their symbolic analysis. PaCon clusters two submissions together if their path conditions are equivalent. PaCon only takes into consideration a program’s semantics. OverCode [13] lets the user visualize and explore different implementations for the same exercise. CodeBERT [11], code2seq [4] and other deep learning models [45] build vector representations of programs by training machine learning models using the programs’ code and ASTs. However, these techniques only consider the programs’ syntax and not their semantics.

Code search techniques [1, 21, 25, 26, 33, 38, 39] repair a given erroneous program using code snippets. However, these methods have no knowledge of the program’s structure where that code fragment came from. Therefore, there is no guarantee that the set of repairs proposed by a code search tool is the minimal set required to fix a program.

Solution-driven program repair use one reference implementation to repair a given incorrect submission [2, 19, 23]. AutoGrader [23] finds potential path differences between the executions of a student’s submission and a reference implementation using symbolic execution. Then, AutoGrader provides feedback to students in the form of counter-examples for each path difference found. Verifix [2] aligns an incorrect program with the reference solution into an automaton. Then, using that alignment relation and MaxSMT solving, Verifix proposes fixes to the incorrect program. Regarding clustering-based program repair tools [15, 24, 32, 41], CLARA [15] was already described, and differences were highlighted in previous sections. SemCluster [32] clusters programs based
on their control flow and data flow features. SemCluster creates vector representations using a test-suite. For each program, it counts the number of times each control flow path is used and tracks the number of occurrences of consecutive values a variable takes during its lifetime. SarfGen [41], used for C# programs, creates program embeddings based on the programs’ ASTs. Then, given an incorrect program, finds the closest correct submission using those embeddings and tries to repair the program by aligning the variables in both programs. More recently, Contractor and Rivero [8] improved CLARA’s matching algorithm to a new graph matching algorithm that is more relax in terms of control flow restrictions. However, this new graph matching algorithm only works for Python programs. Some research has been conducted regarding the use of invariants to promote patch diversity or to help with patch selection on a search-based program repair [5, 9, 42].

In this paper, we compared InvAASTCluster against CLARA’s clustering technique since, to the best of our knowledge, CLARA is currently the only publicly available state-of-the-art clustering-based repair tool for repairing IPAs. However, it would be interesting to evaluate InvAASTCluster on other repair frameworks. Unfortunately, we could not find public implementations for the other tools [2, 12, 24, 32, 41] nor the datasets of IPAs used for their evaluation, except for the ITSP dataset [43].

8 CONCLUSIONS AND FUTURE WORK

In the context of introductory programming assignments (IPAs) in university courses or Massive Open Online Courses (MOOCs), it is possible to collect a large number of correct implementations for the proposed IPAs. Hence, when a student submits an incorrect program, one can take advantage of previously correct submissions to automatically suggest repairs that help the student. However, it is not feasible to analyze all possible previous correct submissions to find an appropriate reference implementation for the repair tool. Therefore, clustering is often used to identify similar program implementations. Afterward, the automated repair tool just analyses a single reference program from each cluster to find the most suitable correction to the student’s incorrect submission.

This work proposes InvAASTCluster, a novel approach for program clustering based on their semantic and syntactic features. InvAASTCluster uses AASTs and invariant-based program representations to distinguish small imperative programs according to their semantics (invariants) and syntax (AAST). Results show that the proposed AASTs and invariant-based representation improve upon syntax-based representations when performing program clustering on several correct student submissions for different programming exercises. Additionally, given an incorrect student submission and a set of correct students’ submissions, InvAASTCluster can also find the closest correct submission to the faulty program using InvAASTCluster’s program vector representations. Furthermore, InvAASTCluster has also been integrated into a state-of-the-art clustering-based program repair framework to evaluate the proposed clustering techniques for repairing IPAs. This evaluation showed that InvAASTCluster outperforms the current state-of-the-art clustering method used in clustering-based program repair. Using InvAASTCluster, the automated repair tool CLARA can repair significantly more IPAs with a better time performance and with a smaller number of program clusters.

To conclude, InvAASTCluster is a program clustering tool based on programs’ invariants and AASTs. InvAASTCluster can be used: (1) to cluster semantically equivalent implementations for programming exercises; (2) by any clustering-based program repair tool; and (3) by any program repair framework that requires a single reference implementation (InvAASTCluster’s closest correct program).

As future directions, we propose to evaluate the new program representations described in this paper (i.e., using AASTs and invariants) as program encodings to use on deep learning models on several tasks such as fault localization or program synthesis. As we expand to consider more
complex programs, we plan to evaluate InvAASTCluster on clustering-based repair tools focused on repairing industrial software. Finally, InvAASTCluster will be evaluated on other clustering-based program repair frameworks with a more permissive repair algorithm than CLARA.

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