Program Repair via Direct State Manipulation

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Abstract. The goal of program repair is to automatically fix programs to meet a specification. We propose a new specification mechanism, direct manipulation, in which the programmer can visualize the trace of a buggy program on a failing input and convey the intended program behaviour by manipulating variable values at some location. The repair problem is to find a program that, on the same input, reaches the location identified by the programmer with variable values equal to the manipulated ones. Since a single program execution under-specifies the overall program behavior, we augment our repair problem with quantitative objectives to find the program that agrees with the specification and is closest to the original one with respect to some distance. We formalize the repair problem, build a program repair tool JDial based on the Sketch synthesizer, and show the effectiveness of JDial on representative buggy benchmarks from introductory programming assignments.

1 Introduction

The goal of program repair [19] is to automatically fix buggy programs to meet a specification that is typically provided in the form of assertions or a set of test cases. In this paper, we propose a new complementary specification mechanism called direct manipulation, in which users can specify the intended program behavior by directly manipulating intermediate variable values in buggy program traces. We propose a workflow in which the user traverses the step-by-step visualization of the execution of the buggy program on a certain input to identify a location where the values of the program variables do not correspond to the ones she expects. At this point, we allow the user to manipulate the variable values at the identified location and modify them. We then treat this manipulation as a specification and use it to find a program that, on the same input, can reach the location identified by the user with the new variable values she provided.

We formalize our repair problem and present a constraint-based synthesis technique for computing program repairs based on direct manipulations. To repair programs in this setting we need to address two key challenges. First, the execution step manipulated by the user in the buggy trace might appear at a completely different point in the trace of the repaired program—e.g., when the repaired program uses a different number of loop iterations from the original program. Second, since a single program execution under-specifies the overall program behavior, there can be many possible repaired programs that agree with the manipulated trace. To address the first challenge, given a manipulated
location ℓ, we design an encoding that “guesses” in what occurrence of the location ℓ in the trace of the repaired program the desired variable values are produced. To address the second challenge, we augment our repair problem with quantitative objectives [5] to prefer repairs that produce execution traces similar to those of the original program.

We implemented our synthesis technique in a tool called JDial, which is built on top of the Sketch [28] synthesizer. JDial supports several repair models and program distances, and can repair Java programs containing loops, arrays, and recursion. We also introduce an algorithm that uses concrete executions to “discover” interpretations of external functions and allows JDial to repair programs containing library functions such as Math.pow. Additionally, JDial also allows users to specify input-output test cases in addition to direct manipulations and is therefore compatible with repair tools like QLOSE [5].

We evaluated JDial on representative benchmarks obtained from QLOSE [5] and several new benchmarks. Our evaluation shows that JDial can quickly repair small Java programs and it produces more accurate repairs than techniques based only on test cases. In particular, even when provided with a single input trace, JDial is able to compute correct repairs for 66% of the programs while techniques based on only test cases always fail.

Contributions. We make the following key contributions.

− We introduce a specification mechanism called direct manipulation together with a corresponding repair problem (§ 3).
− We propose a modular framework based on sketching for repairing programs using direct manipulations (§ 4).
− We instantiate our framework in JDial, a tool that can repair simple Java programs. JDial supports a new algorithm for repairing programs with external functions and an optimized repair technique based on slicing (§ 5).
− We evaluate JDial on 17 representative benchmarks and show JDial computes correct repairs in cases where techniques based on test cases fail (§ 6).

2 Illustrative Example

In this section, we illustrate our approach using an example student attempt to an introductory programming exercise. In this domain, automatic program repair can be used to provide personalized feedback to students [26, 36, 30].

Consider the example in Fig. 1 (a) where a student is trying to write a program largestGap for finding the largest gap in a non-empty array of integers—i.e., the difference between the maximum and minimum values in the array. In the following, we assume that the student has discovered that the program behavior on test [9, 5, 4] is incorrect and is trying to get a suggestion from the repair tool on how she could fix the program.

Repairing via test cases Several program repair tools support test cases as a way to express the correct behaviour of the program. In this case, the student can specify that on the input [9, 5, 4], the correct output should be 5. However, even
```java
int largestGap(int[] x){
    int N = x.length;
    int max = x[N-1];
    int min = x[N-1];
    for(int i=1; i<N-1; i++)
        if(max < x[i])
            max = x[i];
        if(min > x[i])
            min = x[i];
    int res = max - min;
    return res;
}
```

```java
int largestGapFix(int[] x){
    int N = x.length;
    int max = x[N-1];
    int min = x[N-1];
    for(int i=0; i<N-1; i++)
        if(max < x[i])
            max = x[i];
        if(min > x[i])
            min = x[i];
    int res = max - min;
    return res;
}
```

Test case: `largestGap([9,5,4]) = 5`

a) Direct manipulation on failing test case  

b) Repair computed by JDIAL

Fig. 1: Examples of repair using direct manipulation in JDIAL.

the tool QLOSE [5], which can often find correct repairs using a small number of test cases, will return the following wrong modification to line 11:

```
int res = max - min;  \rightarrow  \text{int res = max - min + 4;}
```

QLOSE requires two additional test cases to find the correct repair.

Repairing via direct manipulation Direct manipulations allow programmers to convey more information about the behavior of a test case, rather than only its final output. Our technique is inspired by Guo’s observation [9] that students find it beneficial to visualize concrete program executions and observe discrepancies between the variable values they observe and those they expect. For example, while debugging the `largestGap` program, the student notices that in the first iteration of the loop, right before executing line 8, variable `max` has value 5 instead of the expected value 9. While visualizing the trace, the student can directly modify the value of `max` as shown in the figure and JDIAL will synthesize the program `largestGapFix` consistent with the manipulation (Fig. 1(b))—i.e., when running `largestGapFix` with input `[9,5,4]`, there is a point in the execution where the variable `max` contains value 9 right before executing line 8. Why does this new specification mechanism lead to the desired repair? First, by modifying the program’s trace and its value at line 8, the student implicitly states that certain lines do not need modification—e.g., lines 11 and 12. Second, the modification provides information about an intermediate state of the program that a tool cannot access through just an input/output example. Besides the variable `max`, the student can modify the value of `i` from 1 to 0 or the values of both `i` and `max` at the same position and JDIAL will produce the same repair.

Remarkably, direct manipulation can also help debug partial implementations. Consider, for example, an incomplete version of the program `largestGap` in which lines 8–9 are missing because the student has not implemented the logic for `min` yet. The test case in Fig. 1(a) is essentially useless. On the other hand, the same direct manipulation shown in Fig. 1(a) will yield a good repair.
3 Problem definition

In this section, we define the class of programs we consider, the notion of direct manipulation, and our program repair problem.

3.1 Programs and Traces

We consider a simple imperative language in which a program $P$ consists of a function definition $f(i_1,\ldots,i_q):o$ with input variables $I = \{i_1,\ldots,i_q\}$ and output variable $o$ (NULL for void functions), a set of program variables $V$ such that $V \cap I = \emptyset$, and a sequence of labeled statements $\sigma = s_1 \ldots s_n$. A statement is one of the following: return, assignment, conditional or loop statement. Each statement in $\sigma$ is labeled with a unique location identifier from the set $L = \{\ell_0, \ell_1, \ldots, \ell_p, \text{return}\}$. We assume a universe $U$ of values. We also assume variables are associated with types and assignments are consistent with these types.

Without loss of generality, we assume that executing a return statement assigns a value to the output variable and transfers control to a designated location exit. A program configuration $\eta$ is a pair $(\ell, \nu)$ where $\ell \in L$ is a location and $\nu : I \cup \{o\} \cup V \rightarrow U \cup \{\perp\}$ is a valuation function that assigns values to all variables. The element $\perp$ indicates that a variable has not been assigned a value yet or is out of scope. We write $(\ell, \nu) \rightarrow (\ell', \nu')$ if executing the statement at location $\ell$ under variable valuation $\nu$ transfers control to location $\ell'$ with variable valuation $\nu'$. The execution trace $\pi_P(\nu_0)$ of the program $P$ on an initial valuation $\nu_0$ is a sequence of configurations $\eta_0, \eta_1, \ldots$, where $\eta_0 = (\ell_0, \nu_0)$ and for each $h$, we have $\eta_h \rightarrow \eta_{h+1}$. An execution terminates once the location exit is reached and we only consider programs that terminate on all inputs. We use $\pi_P(\nu_0) = \eta_l$ to denote the configuration at index $l$ and $\pi_P(\nu_0)[l,h]$ to denote the subsequence of configurations between index $l$ and $h$—e.g., $\pi_P(\nu_0)[3,5] = \eta_3 \eta_4 \eta_5$.

Consider the program largestGap in Fig. 1. The input variable set $I$ is $\{x\}$ and the designated output variable is res. The set of program variables is $\{i, \text{max}, \text{min}\}$. Let $\nu_0$ be the initial valuation such that $\nu_0(x) = \{9,5,4\}$ and $\nu_0(w) = \perp$ for every other variable $w$. The execution of largestGap on $\nu_0$ is illustrated on the right (we do not show evaluations of the input variable $x$ as $\nu_h(x) = \nu_0(x)$ for all $h$).

| loc | $\eta_0$ | $\eta_1$ | $\eta_2$ | $\eta_3$ | $\eta_4$ | $\eta_5$ | $\eta_6$ | $\eta_7$ | $\eta_8$ | $\eta_9$ | $\eta_{10}$ |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| N   | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ |
| i   | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ |
| max | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ |
| min | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ |
| res | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ | $\perp$ |

3.2 Repair via Direct Manipulation

We first define the notion of direct manipulation, which allows users to express their intent by modifying variable values in intermediate configurations. We assume a fixed program $P$. A direct manipulation $M$ is a tuple $(\nu_0, k, \nu')$ where $\nu_0$ is an initial valuation, $k$ is an index s.t. $k \leq |\pi_P(\nu_0)|$, and $\nu' : V \cup \{o\} \rightarrow U \cup \{?\}$ is a new partial variable valuation. Intuitively, the manipulation replaces the
configuration $\pi_P(\nu_0)_k = (\ell, \nu)$ at location $\ell$ with the the new partial configuration $(\ell, \nu')$. Notice that a partial configuration cannot change the values of the input variables in $I$ and it can assign a special value $? \in \mathbb{N}$ to certain variables. This value is used to denote that the manipulation “does not care” about the specific values of certain variables. We say that a valuation $\nu$ satisfies a partial valuation $\nu'$, denoted $\nu \vdash \nu'$, iff for every variable $x \in V \cup \{o\}$, if $\nu(x) \neq ?$ then $\nu(x) = \nu'(x)$.

**Example 1.** The direct manipulation in Fig. 1(a) is formally defined as the pair $(\nu_0, 6, \nu')$ where $\nu_0$ is the same as at the end of Section 3.1, $\nu'(max) = 9$ and $\nu'(i) = \nu'(min) = \nu'(o) = ?$. This manipulation, which modifies $\eta_6$, only sets the value of $\max$ to 9 at location 8 and leaves all other variables unconstrained.

Given a program $P$, a direct manipulation $\mathcal{M} = (\nu_0, k, \nu')$ such that $\pi_P(\nu_0)_k = (\ell, \nu)$, we say that a program $P'$ satisfies the manipulation $\mathcal{M}$, if there exists some index $j$ such that $\pi_P(\nu_0)_j = (\ell, \nu_j)$ and $\nu_j \vdash \nu'$. In other words, a program $P'$ satisfies a direct manipulation if there exists some configuration in the execution trace of $P'$ satisfying the manipulated valuation $\nu'$ at location $\ell$. The goal of our repair problem is to find a program that satisfies a given manipulation. In what follows, we fix a repair model, which is a function $\mathcal{R}(\mathcal{P})$ that assigns to a program a corresponding repair space $\mathcal{P}$. The repair space represents a set of programs from which we can draw candidate repaired programs.

**Definition 1 (Repair via Direct Manipulation).** Given a program $P$ and a direct manipulation $\mathcal{M} = (\nu_0, k, \nu')$, the program repair via direct manipulation problem is to find a program $P' \in \mathcal{R}(\mathcal{P})$ that satisfies the manipulation $\mathcal{M}$.

Informally, a direct manipulation $(\nu_0, k, \nu')$ at location $\ell$ is a reachability specification requiring that a configuration $(\ell, \nu')$ is eventually reached along an execution from the initial valuation $\nu_0$. This specification mechanism is orthogonal to that provided by assertions, which require a property $\varphi$ at location $\ell$ to be an invariant specification—i.e., each time an execution reaches location $\ell$, the property $\varphi$ should hold. For instance, in Figure 1 (a), placing the assertion $\max = 9$ at location 8 would specify that the value of $\max$ should be 9 at location 8 across all loop iterations in an execution. The astute reader may suggest that for some suitably chosen predicate condition over the loop counter, an assertion of the form condition $\Rightarrow (\max = 9)$ at location 8 could encode the direct manipulation in Figure 1. However, a direct manipulation does not explicitly indicate what such a predicate condition should be. In particular, a direct manipulation does not specify what the manipulation-satisfying index $j$ should be.

**Handling test cases** Definition 1 can be generalized to the problem of repairing a program $P$ given a direct manipulation and a set of tests. A test $t$ is a pair $(\nu^I, \nu^O)$, where $\nu^I$ is a valuation over the input variables $I$ and $\nu^O$ is a valuation over the output variable $o$. Let $\nu_0^I$ denote an initial valuation such that $\nu_0^I(w) = \nu^I(w)$ if $w \in I$ and otherwise. Program $P$ satisfies a test $t$ if the value of the output variable $o$ at the end of an execution $\pi_P(\nu_0^I)$ of $P$ on initial valuation $\nu_0^I$ is $\nu^O$, i.e., if $j = |\pi_P(\nu_0^I)| - 1$, $\eta_j = (\ell, \nu)$ and $\nu(o) = \nu^O$. Program $P$ satisfies a
set of tests \( T \) if it satisfies all the tests \( t \in T \). The repair problem is then to find a program that satisfies both the direct manipulation and the tests.

Cost-aware Repair Among the many programs that satisfy a given manipulation we would like to pick the “best” one. To define what it means for a candidate repaired program to be better than another, we draw upon the notions of program distances proposed in [5]. We define two types of distances: syntactic and semantic distances. Given a program \( P \), a syntactic distance is a function \( f_{\text{syn}}^P : \mathcal{P} \rightarrow \mathbb{N} \) that maps each program in the repair space to a quantity capturing its syntactic similarity to the original program \( P \). We define semantic distances using distance functions over execution traces. Let \( \text{dist}(\pi, \pi') \) denote a distance function mapping a pair of traces to a non-negative integer. Intuitively, \( \text{dist} \) captures the similarity between execution traces of \( P \) and \( P' \) on the same initial valuation \( \nu_0 \). Given a program \( P \) and a direct manipulation \( M = (\nu_0, k, \nu') \), a semantic distance function \( f_{\text{sem}}^{P,M} : \mathcal{P} \rightarrow \mathbb{N} \) maps a repaired program \( P' \) to \( \text{dist}(\pi_P(\nu_0)[0,k], \pi_P'(\nu_0)[0,j]) \) capturing the similarity between the manipulated trace \( \pi_P(\nu_0)[0,k] \) of \( P \) and the corresponding manipulation-satisfying trace \( \pi_P'(\nu_0)[0,j] \) of \( P' \) with manipulation-satisfying index \( j \). An aggregation function \( \text{Aggr} : \mathbb{N} \times \mathbb{N} \rightarrow \mathbb{N} \) is used to combine the two distance functions.

Example 2. An example of syntactic distance between two programs \( P \) and \( P' \) is the number of node edits needed to transform the abstract syntax tree \( P \) into the one \( P' \). According to this distance, the change from \( i=1 \) to \( i=0 \) shown in Figure 1 has syntactic distance 1. An example semantic distance is the sum of the differences in variable valuations in program configurations of the execution traces \( \pi_P(\nu_0)[0,k] \) and \( \pi_P'(\nu_0)[0,j] \) (with \( j \) as defined above).

For a program \( P \) and direct manipulation \( M \), we can define the cost of a repaired program \( P' \) as \( \text{cost}(P') = \text{Aggr}(f_{\text{syn}}^P(P'), f_{\text{sem}}^{P,M}(P')) \). The following definition can be generalized to incorporate a set of tests.

Definition 2 (Cost-aware Repair via Direct Manipulation). Given a program \( P \) and a direct manipulation \( M \), the cost-aware program repair via direct manipulation problem is to find a program \( P' \in R_M(P) \) that satisfies the manipulation \( M \) and such that, for every \( P'' \in R_M(P) \) that satisfies the manipulation \( M \), we have \( \text{cost}(P') \leq \text{cost}(P'') \).

4 JDIAL’s architecture

In this section, we describe the architecture of JDIAL and the sketching-based approach JDIAL employs to repair programs (Figure 2).

JDIAL takes as input a buggy program, a direct manipulation on an input trace, and (optionally) a set of test cases (left of Figure 2). As described in Section 3, the repair problem is defined using four components: a repair model, a syntactic distance function, a semantic distance function, and a cost-aggregation function. In JDIAL, these components are modular and defined independently.
from the underlying synthesis engine (grey boxes at the top of Figure 2). The repair model is given as a program GetRepairSpace that, given a program, returns a sketched version of it—i.e., a program with unknown holes of the form ?? in Figure 2, this program simply replaces each constant with a hole. By instantiating the holes in the sketched program with concrete values we obtain a program in the repair space. The syntactic distance is given as a program that computes a non-negative integer based on the values of the holes in the sketched program—e.g., how many constants were changed or by how much they were changed. The semantic distance is given as a program that computes a non-negative integer based on the value of two traces—e.g., the Hamming distance.

4.1 From Program Repair to Sketching

To solve the repair problem, JDIAL computes a sketched program together with a set of assertions (blue box in Figure 2). The solution to this sketched program—i.e., values for the holes that satisfy the assertions and minimize the given objective function—is the solution to the program repair problem.

**Background on sketching** Program sketching is a technique for specifying a parametric set of programs. This is done by allowing programs to contain holes (denoted by ??). When one provides a specification—e.g., test cases, assertions, minimization objectives—the sketching problem is to find (typically integer) values of the holes that satisfy the given specification. State-of-the-art sketching tools support complex program constructs, such as arrays, strings, and recursive functions, as well as complex specification mechanisms, such as Boolean assertions and quantitative optimization constraints over the values of the holes [28].

**Computing distances and guessing trace lengths** The GetRepairSpace component, given the buggy program, adds holes to generate a sketched program encoding the repair space—e.g., y = ??_1 * x + ??_2 * y + ??_3 in Figure 2 (blue-box). JDIAL then generates a function that uses the values placed in the holes to compute the syntactic distance (Figure 2(top)).
To compute the semantic distance JDIAL symbolically extracts program traces by instrumenting the sketched program with a counter to measure the length of the trace, an array to record the values of each variable in the original program, and an array for the line numbers. After executing each sketched instruction, the arrays are updated to reflect the current variable values (Figure 2(blue-box)). JDIAL then extract the traces from such arrays and uses them to compute the semantic distance.

The key difficulty in encoding our repair problem is that there can be many ways to “align” the location manipulated by the user with a location in the sketched program—e.g., the execution of one repaired program might reach the desired manipulated value the second time the manipulated location is visited, while another repair might reach the desired value the tenth time the manipulated location is visited. JDIAL must be able to consider all these possibilities.

Example 3. Consider the manipulation described in Fig. 1(a). The execution of the repaired program largestGapFix presented in Fig. 1(b) on input [9, 5, 4] hits the manipulated location with max=9 the first time line 8 is traversed. However, another correct repair which changes the loop in line 5 to i=N-2; i>=0; i--, hits the manipulated location with max=9 the second time line 8 is traversed.

Our key idea is to introduce an existential unknown variable—i.e., another hole—in our sketched program to guess at what visit time the manipulated line is reached with the variable values provided by the user. Concretely, we define a global variable int visit_time = ?? to guess the number of visits of the manipulated line and modify the sketched program right before the sketched version of the manipulated line to interrupt the trace at the correct time (see Fig. 3). Thus, every time the manipulated line is reached, visit_time is decremented and, when the counter hits zero, the execution has reached the guessed number of visit times.

Finally, JDIAL adds assertions to guarantee the sketch solution satisfies the manipulation and a minimization objective to ensure the returned solution is optimal with respect to the given distances (see right of blue box in Fig. 2).

5 Implementation and optimizations

JDIAL is composed of a frontend, which allows to visualize program traces and manipulate intermediate states, and a backend, which repairs the manipulated programs. JDIAL’s frontend uses the tool java_jail to extract program traces and JavaScript, together with the library CodeMirror, to render the user interface and communicate with the backend. JDIAL’s backend uses the synthesizer

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1 We assume that the length of the trace in the repaired program is at most twice the length of the original trace and we use this assumption to initialize the length of the arrays. This constant is parametric and can be modified.
SKETCH [28] to solve the sketched programs we generate using the technique proposed in Section 4. JDIAL can repair Java programs over integers, characters, Booleans, and arrays over these basic types. In its default mode, JDIAL only tries to repair statements in the function in which the manipulated line appears. In this section, we describe the concrete repair model and distance functions JDIAL uses as well as several optimizations employed by JDIAL.

5.1 Repair Model and Syntactic Distance

JDIAL supports complex repair models—e.g., it can allow statements to be added to the program. However, overly expressive repair models will often lead to undesired repairs that overfit to the given manipulation. In fact, existing repair tools for introductory programming assignments typically employ several repair models, each tailored to a particular programming assignment [26, 22].

Since in our application domain we do not know a priori what program the programmer is trying to write, JDIAL’s default repair model only allows to rewrite constants in linear arithmetic expressions (see Appendix A for details). First, any variable in any expression is multiplied by a hole $??_b$ that can only take values from the set $\{-1, 0, 1\}$. These holes can be used to remove variables and negate their coefficients. Second, the term $\sum_{v \in V} ??_b v + ??$, where $V$ is the set of variables, is added to each expression appearing in an assignment or in a Boolean comparison. These terms can be used to add new variables, further increase/decrease the coefficients of variables appearing in the expression, or add new constants—e.g., turn $x<0$ into $x>y$. This repair model permits modifications of multiple expressions and it subsumes the default error model of the AutoGrader tool, which, despite its simplicity, was shown to be able to repair 30%-60% of edX student submissions depending on the problem type [26].

JDIAL’s syntactic distance computes the difference between the synthesized hole values and the original ones. For example, in the expression $??_b x < 0 + \sum_{v \in V} ??_b v + ??$ (corresponding to original expression $x<0$), the original value of the first hole $??_b$ is 1, while the original value of all the other holes is 0. The syntactic distance is the sum of the absolute difference between each hole’s synthesized value and the original one. Intuitively, this distance penalizes modifications that introduce new variables and modify constants by large amounts.

5.2 Semantic Distance over Traces

When computing the distance from the original program traces, JDIAL ignores the variables that have been manipulated because they are likely to contain “incorrect” values that are not necessary to preserve. JDIAL first computes the restricted traces where the values of the manipulated variables are omitted and then uses a modified version of the Hamming distance to compute their distance. In the following definitions, we assume Boolean tests return 1 when true and 0 when false. Given two configurations $\eta = (l, \nu)$ and $\eta' = (l', \nu')$ over a set of variables $V$, the distance between the two configurations is defined as $H(\eta, \eta') = (l \neq l') + \sum_{w \in V} \nu(w) \neq \nu'(w)$. Finally, JDIAL computes the distance between two
Fig. 4: Given an example with an incorrect for-condition and an input test (a), JDIAL uses the execution of `sumPow` on the test to learn an initial partial interpretation of the function `Math.pow` (b). JDIAL then produces a proposed repair and guesses the interpretation of `Math.pow` to be such that `Math.pow(2,3)=14` (c). After executes `Math.pow` in Java, JDIAL discovers that `Math.pow(2,3)=8`, and refines the interpretation of `Math.pow` for the next round of repair.

traces $\pi = \eta_1 \cdots \eta_s$ and $\pi' = \eta'_1 \cdots \eta'_t$, where $m = min(s,t)$ and $M = max(s,t)$ as the quantity $H(\eta_1, \eta'_1) + \cdots + H(\eta_m, \eta'_m) + M - m$.

Example 4. Consider again the example described in Figure 1. The restricted trace of the repaired program up to the manipulation-satisfying index has distance 3 from the original trace since it only changes the value of the variable $i$ in the last three steps and it has the same length as the original program trace.

JDIAL contains other implementations of trace distances—e.g., longest common subsequences. Since the distance presented above yields good results and performance in practice, we use it as default and use it in our experiments. JDIAL aggregates the syntactic and semantic distances by taking their sum.

5.3 Handling External Functions

JDIAL employs a new Counterexample-Guided Inductive Synthesis (CEGIS) scheme to repair programs that contain external functions for which semantics might be unknown or expensive to encode directly in Sketch. Given the input program with an external function `ext` and the manipulated trace, JDIAL creates a sketched program that assigns a partial interpretation to the external function using the set of concrete values obtained from the input trace execution—i.e., for every call of the function observed in the input trace. JDIAL then computes a repair for the sketched program using the partial definition of `ext` it obtained from the trace. If repairing the program requires knowing the interpretation of `ext` on inputs that have not been observed yet, JDIAL lets Sketch “guess” an interpretation for the function `ext` on such inputs. JDIAL can then execute the function `ext` and check whether the guesses were correct. If they are not correct, JDIAL modifies the new sketched program to incorporate the partial interpretation to the external function `ext` on the newly discovered inputs. The process continues until JDIAL finds a repair that respects the semantics of `ext`. 
Example 5. Consider the program `sumPow` in Fig. 4(a), which should compute the sum of powers of 2 up to x, but instead it only computes the sum up to x-1. By running the program on the given input 3, JDIAL can obtain the output of the `Math.pow` function on input values 1 and 2, and constructs a sketch function that describes a partial interpretation of `Math.pow` as shown in Figure 4(b). To repair the program, JDIAL needs to change the condition of the for loop, but this repair requires knowing the output of the function `Math.pow` on arguments (2,3) and our partial interpretation of `Math.pow` does not contain this information. JDIAL synthesizes a repair for the function `sumPow` and, while doing so, it assigns an interpretation to the inputs for which the behaviour of the function `Math.pow` is unknown (Figure 4(c)). JDIAL then uses the concrete execution of the function `Math.pow` to check whether the synthesized interpretation is incorrect, and in this case it modifies the partial interpretation of `Math.pow` in the sketched program.

5.4 Additional Features and Optimizations

We discuss additional features and optimizations supported by JDIAL.

Specified repair range. Since the programmer might want to prevent JDIAL from modifying certain program statements, JDIAL’s frontend allows the programmer to specify what statements the tool is allowed to modify.

Single statement repairs. Since most repairs only require to modify a single statement, JDIAL supports this restricted repair model and it uses an optimized solver that, for each line of code, builds a separate sketched program that is only allowed to modify that line. The separate sketched programs are then solved in parallel and JDIAL outputs the repair with the least aggregate cost.

For each individual sketch that can only modify a certain line of code, JDIAL uses a data flow analysis based on program slicing [35] to summarize parts of the program for which the corresponding traces will not be affected by the code modification. Concretely, let $\ell_M$ be the location at which the manipulation is performed and $\ell_R$ be the location JDIAL is allowed to modify. By computing a backward slice of the manipulated location $\ell_M$, we obtain

```java
// input: [3,2,7]
int[] subLargestGap(int[] a) {
    int N = a.length;
    int min = max = a[0];
    for (int i = 0; i < N; i++) {
        if (max < a[i]) max = a[i];
        if (min > a[i]) min = a[i];
    }
    int largestgap = max - min;
    for (int i = 1; i < N; i++) {
        a[i] = a[i] - largestgap;
    }
    return a;
}
```

```java
void sliced(int[] a) {
    int N = 3;
    int largestgap = 5;
    for (int i = 1; i < N; i++)
        a[i] = a[i] - largestgap;
    return a;
}
```

Fig. 5: Program `subLargestGap` and its sliced version when the manipulation happens at line 13 and only line 11 can be modified.
the statements that can affect the values of the manipulated variables. Similarly, only statements that are reachable from location $\ell_R$ in the control-flow graph of the program are affected by modifications to line $\ell_R$. Finally, the intersection of the two sets gives us the statements where variable values may vary as a result of a repair. All other statements are irrelevant and can be removed or summarized.

Example 6 Consider the program `subLargestGap` in Fig. 5 that returns a new array obtained by subtracting the largest gap of the input array from all its elements. This program contains a mistake in the second for loop. Assume a student is trying to fix it by manipulating the variable $\text{a}[0]$ at location 11 on input $[3,2,7]$ and that the repair model only allows modification to location 9. The backward slice of location 11 contains all the statements in the program except the return statement and the lines 9 to 12 are the only lines reachable from location 9. Using this information, JDIAL summarizes all other statements’ values. For example, the whole computation of the variable `largestGap` is replaced by the constant assignment `largestGap=5`.

6 Evaluation

We evaluate the effectiveness of JDIAL through the following questions.

Q1 Can JDIAL produce good repairs more often than test-based techniques?
Q2 Is the optimized version of JDIAL presented in Sec. 5.4 effective?
Q3 How sensitive is JDIAL w.r.t. the location of the manipulation?
Q4 Can JDIAL repair programs that contain external functions?

We perform our evaluation on 17 Java programs: 12 from QLOSE [5] and 5 new programs. The programs from [5] are small introductory programming assignments and programs from repair literature (see Appendix B for details).

Table 1 shows detailed metrics for each benchmark and the average runtime of JDIAL when performing repair on five randomly generated failing inputs. All experiments were performed on an Intel Core i7 4.00GHz CPU with 32GB/RAM.

Comparison to Test-based Repair. We compare JDIAL against the tool QLOSE to see if repair via direct manipulation can find correct repairs more often than test-based repair. We compare against QLOSE because it is the only repair tool that uses semantic distances and it produces accurate repairs from a small number of test cases more often than tools that only use syntactic distances [5].

For each benchmark, we randomly generate 5 input tests that result in incorrect outputs. For each failing test, we run QLOSE using the test as a specification and run JDIAL by manually constructing a manipulation: we identify the first location in the execution trace where a variable has the wrong value and modify it to the correct one. Figure 6 illustrates the results of this comparison (JDIAL and QLOSE bars). JDIAL generates the intended repairs in 66% (56/85) of the cases while QLOSE never produces a correct repair. In particular, when given only one test case, QLOSE always modifies the return statement of the program.

We perform another study where, for each previous experiment, we provide JDIAL and QLOSE with an additional (failing or passing) test—i.e., we provide
Table 1: Effectiveness and performance of JDial. **Success** denotes the number of tests (out of 5) for which we get a desired repair. **\( \otimes \)** denotes out of memory.

| Problem     | LOC | Vars | Success | Trace Length | Time [sec] | Time single line [sec] | JDial \(_1\) | JDial \(_2\) |
|-------------|-----|------|---------|--------------|------------|------------------------|------------|------------|
| largestGap-1.1 | 7   | 4    | 3       | 11           | 3.8        | 1.6                    | 1.0        |            |
| largestGap-1.2 | 7   | 4    | 4       | 10           | 2.2        | 0.8                    | 0.6        |            |
| largestGap-2  | 7   | 4    | 2       | 15           | 4.2        | 1.1                    | 0.5        |            |
| largestGap-3.1 | 7   | 4    | 4       | 10           | 1.8        | 1.1                    | 1.0        |            |
| largestGap-3.2 | 7   | 4    | 4       | 10           | 2.8        | 1.0                    | 0.6        |            |
| Qlose \[6\]    |     |      |         |              |            |                        |            |            |
| tcas           | 10  | 4    | 0       | 7            | 0.8        | 0.4                    | 0.4        |            |
| max3           | 5   | 3    | 5       | 3            | 0.5        | 0.3                    | 0.3        |            |
| iterPower-1    | 5   | 3    | 4       | 14           | 0.4        | 0.6                    | 0.4        |            |
| iterPower-2    | 5   | 3    | 5       | 14           | 0.7        | 0.4                    | 0.3        |            |
| ePoly-1        | 6   | 4    | 4       | 12           | 4.6        | 3.7                    | 1.3        |            |
| ePoly-2        | 6   | 4    | 3       | 12           | 2.5        | 1.7                    | 0.9        |            |
| multIA         | 4   | 4    | 5       | 9            | 1.3        | 0.8                    | 1.1        |            |
| ePoly-3        | 7   | 4    | 4       | 13           | 2.9        | 2.8                    | 2.5        |            |
| max4           | 5   | 4    | 4       | 12           | 3.1        | 1.3                    | 0.6        |            |
| bubbleSort     | 7   | 5    | 4       | 12           | 3.1        | 1.3                    | 0.6        |            |
| subLargestGap  | 13  | 6    | **X**   | 35           | **X**      | **X**                  | **X**      | 0.7        |
| maxMin         | 13  | 6    | **X**   | 37           | **X**      | **X**                  | **X**      | 0.9        |

Fig. 6: JDial vs Qlose. Additional test provided in JDial\(_+\) and Qlose\(_+\).

Qlose with two tests and JDial with one test and one manipulation. Figure 6 illustrates the results of this comparison (cf. JDial\(_+\) and Qlose\(_+\) bars). JDial generates the intended repairs for 75% (64/85) of the cases while Qlose produces the correct repairs on 58% (49/85) of the cases. While Qlose performs better than when given a single test, for every input on which Qlose produces the correct repair, JDial also does so. Remarkably, when given a single manipulation and nothing more, JDial produces correct repairs more often than Qlose, even when the latter is provided with 2 tests. To answer Q1, JDial produces meaningful repairs more often than techniques that only use tests.

Before concluding, we explain why both tools performed poorly on some benchmarks. For the tcas program, the desired fix modifies an expression by adding a large constant that can only be synthesized from a very specific test case. subLargestGap and maxMin are too large. For the instances for which
JDIAL produces the incorrect repair, we evaluate whether JDIAL produces correct repairs if it is allowed further “attempts”. Whenever an undesired repair is generated at a location $\ell$, we disallow JDIAL to repair location $\ell$ again or reject the proposed repair and ask for a different one. This approach repairs an additional 6 failing tests across all programs with an average of 2.2 user interactions.

**Optimizations for Single-line Repairs.** We repeat the previous experiment using the single-line repair model described in Sec. 5.4. We refer to the version of JDIAL with this restricted repair model as JDIAL$_1$ and its optimized version as JDIAL$_1^o$. Since in our previous experiments JDIAL always finds a repair that only involves a single line, both JDIAL$_1$ and JDIAL$_1^o$ find the same repair. The last two columns of Table 1 show the running times. JDIAL$_1$ is generally faster than the version of JDIAL that uses the more complex repair model. However, the optimized version JDIAL$_1^o$ is on average 1.37x faster than JDIAL$_1$. Moreover, for subLargestGap and maxMin, JDIAL$_1^o$ finds repairs in <1 second while JDIAL$_1$ times out. The improvement is due to the slicing-based data-flow analysis, which, can reduce the number of lines in the sketched program from 25 to 8.

To answer **Q2**, the optimization from Sec. 5.4 is beneficial for single-line repairs. This repair model is very practical and our results hint that our slicing technique can make JDIAL scale to larger programs.

**Sensitivity of Manipulated Location.** One of the key aspects of JDIAL is that the user has to find a “good” location to perform the desired repair. In this experiment, we evaluate how sensitive JDIAL is with respect to the location choice. We consider the experiment we performed against test-based repair and for each test case on which JDIAL and JDIAL+ successfully found a correct repair, we then perform the following analysis: if the manipulation was performed at step $i$ in the program trace, we measure after how many steps the generated repair is “lost” —i.e., we compute the smallest $k$ for which performing the manipulation at position $i+k$ would yield a wrong repair.

Figure 7 shows the results. In 80% of the cases, if JDIAL is provided only with a manipulation and the manipulation is performed one step later, JDIAL returns an incorrect repair. However, when provided with one additional test case JDIAL returns the correct repair in 80% of the cases, even when the manipulation is performed 5 steps after the ideal location. Even in these extreme conditions, JDIAL returns correct repairs more often than QLOSE does when provided with two test cases. To answer **Q3**, JDIAL is sensitive with respect to the manipulation location only if no additional tests are provided, but it is still more precise than repair via test cases.

**Ability to Handle External Functions.** We evaluate if JDIAL can repair programs with external functions. ePoly-1 and ePoly-2, contain the function
Math.pow and JDIAL is able to produce a repair for them using between 2 and 5 iterations (average 4.2), of the CeGIS algorithm presented in Sec. 5.3.

To better evaluate the algorithm, we design two families of benchmarks that use auxiliary functions. The first family of programs tries to compute $\sum_{i=0}^{n} \text{Math.pow}(2, i)$ for values of $n$ between 2 and 8. The bug in this benchmark is the one shown in Figure 4. For inputs 2 and 3, JDIAL can find the correct repair that is compliant with the external function after 2 CeGIS iterations, while for inputs 4 through 8, JDIAL requires 3 iterations. The second family of programs computes the maximum value in an array using the Math.max function for different incorrect initializations of the variable max. In this case, the size of the initial constant affects the number of required CeGIS iterations. While incorrectly initializing max to 2 only requires a couple of iterations to produce the correct repair, if we incorrectly initialize max to 100, computing the repair requires guessing many new interpretations of the function Math.max that did not appear in the original trace, resulting in more than 90 iterations.

To answer Q4, JDIAL can repair programs that contain external functions, but in certain pathological cases it requires many CeGIS iterations.

7 Related Work

Direct manipulation Direct manipulation is an old concept [25] and several drawing editors [33, 24, 11] provide programming capabilities and at the same time allow the user to interact with the graphics being displayed by the code. SKETCH-N-SKETCH [4, 10] uses a simple form of program synthesis to combine direct and programmatic manipulation of scalable vector graphics (SVG), where constants in the program can be modified conforming to the direct manipulations. SKETCH-N-SKETCH and JDIAL are somewhat incomparable due to the different domains, but we describe some high-level differences between the two tools. SKETCH-N-SKETCH can only rename constants defined at the top of the program and, unlike JDIAL, cannot handle complex updates involving changes in the program structure—e.g., replacing $x = y$ with $x = y - z$. Moreover, SKETCH-N-SKETCH employs heuristics to identify the “right” fix, while JDIAL identifies fixes that are optimal with respect to syntactic and semantic distances.

Wolverine [32] allows direct manipulation of data-structure transformations. In Wolverine, the user can modify a graphical abstract representation of a data structure such as a linked list and the tool will attempt to find a program modification consistent with the modification. Similar to SKETCH-N-SKETCH, Wolverine’s technique is specific to certain families of data structure transformations and relies on the graphical abstraction used for the manipulation.

CODEHINT [7] synthesizes simple Java expressions—e.g., library calls—at user-set breakpoints using partial specifications—e.g., variable types. It uses information from the execution to construct expressions of a user-provided type. CODEHINT is different from JDIAL in three main aspects: (i) CODEHINT helps programmers auto-complete function calls given some expected type at a given location, whereas JDIAL repairs the original program using a global analysis.
(iii) CodeHint can only synthesize one expression at a time due to its specific interaction mode. (iii) CodeHint performs brute-force search while JDial uses constraint-based search with optimization objectives.

**Personalized education** There are many tools for teaching programming that help with grading (see [29] for a survey), personalized feedback [21, 8, 13, 26, 5, 22], and visualization [9]. Several works have dealt with transforming repair tools into feedback generators [30]. Here, we discuss tools relevant to our work.

**AutoGrader** [26] and Qlose [5] can compute program repairs for incorrect student solutions to introductory programming assignments. These systems require the teacher to provide a reference implementation or a comprehensive set of test cases while JDial also allows students to discover potential repairs using direct manipulations. AutoGrader [26] computes syntactically minimal repairs while Qlose computes syntactically and semantically minimal repairs based on a set of test cases. JDial extends Qlose’s technique to compute minimal program repairs based on prefix traces and manipulated states. In particular, JDial encodes the problem of finding good stop points for aligning partial program traces that is novel in our setting of direct manipulation of variables.

**Program repair** This topic has been studied extensively and researchers have proposed techniques based on constraint-solving [20], abstractions [17], and genetic algorithms [1, 16]. JDial falls in the first category, but it would be interesting to investigate the effectiveness of the other techniques in our domain. There are approaches that find repaired programs that are syntactically close [23, 18] or semantically close [34] to the original program. It was demonstrated in [5] that repairs generated using a combination of syntactic and semantic program distances are, in general, more desirable. Hence, JDial chooses this last approach.

Existing tools use test cases [20, 5], logic specifications [15], or reference programs [26]. Direct manipulation “augments” a test case by allowing the user to specify intermediate information about the run of the program on a certain input. Moreover, direct manipulations can be used to debug partially written implementations. Finally, it is important to note that direct manipulation is not directly expressible using assertions or test cases: while an assertion at a certain location is valid if every time the location is traversed the predicate in the assertion is true, a direct manipulation at a certain location only requires that at some point in the trace the variables evaluate to the manipulated values at that location.

Several repair tools use fault localization to find likely locations to modify [2, 12, 3, 14]. Extending fault localization techniques to our setting is another interesting research direction. The work on angelic debugging [3] is particularly relevant to JDial, where the technique infers possible faulty expressions in a program by replacing them with an alternate concrete value (oracle) that makes all the tests pass. However, the burden on repairing the program with the correct expression still lies with the programmer.

The CEGIS refinement of external functions presented in Sec. 5.3 is related to the notion of Sketch models [27], which allow one to specify certain properties (such as associativity, idempotence, etc.) to provide richer interpretations to
uninterpreted functions. In contrast, JDIAL iteratively builds a model of the auxiliary function directly from the repair process.

8 Conclusion

We presented a new specification mechanism called direct manipulation, which allows programmers to modify variable values at an intermediate point in a failing trace to indicate what variable values were expected. We built the tool JDIAL that can repair simple Java programs to satisfy direct manipulations specified by the programmer. Finally, we showed that direct manipulations lead to more accurate repairs than those computed using only test cases. While our approach has shown promising results on simple programs appearing in introductory programming assignments, this paper is just the first step towards a new, exciting direction and many research questions remain open. Our next steps include investigating more complex manipulation techniques that can be used by real programmers on large scale programs and designing user studies to assess whether students/programmers are receptive to this novel specification paradigm.

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A Repair Model

Figure 8 illustrates JDIAL’s default repair model and Figure 9 illustrates an example of how the repair model generates a Sketch from a program.

\[
\begin{align*}
    r(x = e) & \rightarrow x = r(e) + \left( \sum_{v \in V} b_v + ? \right) \\
    r(e_1 \text{ bop } e_2) & \rightarrow r(e_1) \text{ bop } r(e_2) + \left( \sum_{v \in V} b_v + ? \right) \\
    r(\text{return } e) & \rightarrow r(e) + \left( \sum_{v \in V} b_v + ? \right) \\
    r(e_1 + e_2) & \rightarrow r(e_1) + r(e_2) \\
    r(c*e) & \rightarrow c \cdot (r(e) + \left( \sum_{v \in V} b_v + ? \right)) \\
    r(c) & \rightarrow c \\
    r(x) & \rightarrow ??b x \\
    r(x[e]) & \rightarrow ??b x [??b * e + ??] \\
    r(f(e)) & \rightarrow ??b f(e)
\end{align*}
\]

Fig. 8: JDIAL’s repair model.

B Detailed Benchmark Description

All benchmarks and the corresponding Sketch files are available at this url: https://tinyurl.com/yd6dp3dx. The set contains three variants of largestGap (§ 2), which is used in the Microsoft CodeHunt platform [31]. For two of the largestGap benchmarks, largestGap-1 and largestGap-3, we further split the programs into two sub-benchmarks denoted with the suffixes .1 and .2. These are benchmarks in which the students has two logically separate errors that would require many test cases to be fixed. We use .1 to denote the original
version of the benchmark and assume the task is to fix the first error in the program and .2 to denote the same benchmark in which the first bug has been fixed and the task is to fix the second error. The tcas-semfix program is a toy traffic collision avoidance system from [20]. The max, iterPower, ePoly, and multIA problems are taken from the Introduction to Python Programming course taught on edX [6]. Two of the new programs we consider are variations of QLOSE benchmarks. The other three bubbleSort, subLargestGap, and maxMin are larger programs that contain multiple loops, which are more complex than the benchmarks considered in [5].