GENERATING TEST INPUTS FROM STRING CONSTRAINTS WITH AN AUTOMATA-BASED SOLVER

by

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The following individuals read and discussed the thesis submitted by student Marlin Roberts, and they evaluated the presentation and response to questions during the final oral examination. They found that the student passed the final oral examination.

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ABSTRACT

Software testing is an integral part of the software development process. To test certain parts of software, developers need to identify inputs that reach those parts. Data and control dependencies make this a non-trivial task, and as the complexity of software increases it becomes more difficult to manually derive such inputs. Due to complex data manipulations, this process is even more challenging for programs with string inputs, such as security applications. Thus, automated reachability test input generation for string data types is an important research area.

Symbolic Execution is a path-sensitive static program analysis technique that can automatically generate conditions for inputs that reach a given program location. Commonly, such conditions are encoded as automata that describe a set of strings at that location. Automata result from string operations applied to inputs along that path. However, these automata do not necessarily correspond to string inputs that result in string values at the program location. To find those input values, we need to undo the effects of string operations through backward analysis. The intricate relationships between symbolic string values complicate this process. These relationships are due to non-injective string operations and data-flow dependencies of string values.

This thesis presents a novel method for test input generation for automata-based string constraints. It uses single-track automata along with novel computational techniques to perform inverse string operations. Empirical evaluations on a set of benchmarks have shown this method to be effective in solving automata-based string constraints from real-world applications.

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SPF	Symbolic Pathfinder
SE	Symbolic Execution
PC	Path Conditions
SAT	Satisfiable
UNSAT	Unsatisfiable
FSA	Finite State Automata
SMT	Satisfiability Modulo Theory
TCG	Transposed Constraint Graph

LIST OF SYMBOLS

$\mathcal{A}$	Finite State Automata
$\mathcal{L}(\mathcal{A})$	Language of Finite State Automata
Σ	Alphabet of Finite State Automata
k	Length of String Accepted by Finite State Automata
ε	Empty String

SECTION 1

INTRODUCTION

Once relegated to a brief ad-hoc effort, software testing has become a well-established systematic software development process. Primary factors driving the adoption of testing are the increased cost of software defects that can cause security breaches and failures of safety critical systems. As software testing became an integral part of software development, software bacame more complex with intricate data and control dependencies. This has caused an increase in the test case generation effort, and in-particular identifying test cases that reach specific locations in code. With simpler software it was feasible for a programmer to reason about test inputs that reach program locations, however with complex software the programmers require automated approaches to aid in generating test inputs for code reachability.

In response to these challenges, researchers leverage static program analysis techniques such as *Symbolic Execution* (SE) [5,12] to generate test inputs [5,7,17], detect security vulnerabilities, and find program defects. When used to generate inputs, SE helps with finding a feasible path to the targeted location, which needs to be executed by a test. However, it remains difficult to analyze and generate test cases for programs that manipulate variables of complex data types such as strings, and have variables entangled in non-trivial computations.

This work investigates approaches that improve test input generation for Java String manipulating programs using SE techniques. Before explaining challenges that this work addresses, the next section details the SE approach to test input generation for Java string programs. It starts with an overview of SE testing and continues with modeling sets of strings as automata.

1.1 Symbolic Execution

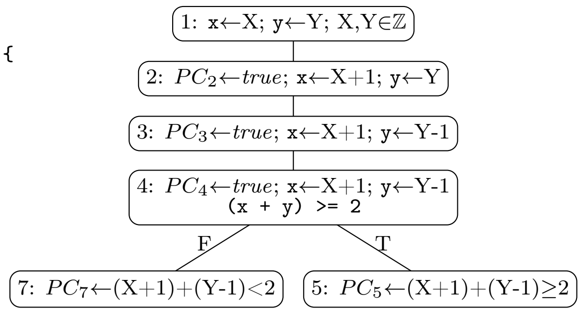
SE is a path-sensitive static program analysis technique that simulates the execution of a program on symbolic inputs. In general, the process consists of interpreting the code to determine the values that variables may take and determining the condition (or *constraint*) that defines a path. To use it as a white-box test case generator, a SE engine sends that constraint to a solver and asks to return a satisfiable solution. An overview of the process follows, starting with the introduction of symbolic variables.

1.1.1 Symbolic Variables

Figures 1.1 and 1.2 present examples of SE on Java methods with integer and string inputs, respectively. SE treats program input variables as symbolic values by using *Symbolic Variables* to represent all possible concrete values that a program input variable may take. Figure 1.1b shows the assignment of symbolic variables to integer arguments `x` and `y` at the top of the symbolic execution tree: ($\mathtt{x} \leftarrow X$) and ($\mathtt{y} \leftarrow Y$). Figure 1.2b shows similar assignments for strings `s1`, `s2` and `s3`.

```
1 public void intEx (int x, int y) {
2   x = x + 1;
3   y = y - 1;
4   if ((x + y) >= 2 ) {
5     // true branch
6   } else {
7     // false branch
8   }
9 }
```

(a) Method with integer inputs

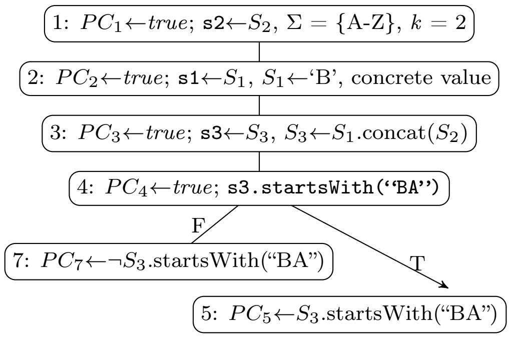

1: x←X; y←Y; X,Y∈ℤ
2: PC_2←*true*; x←X+1; y←Y
3: PC_3←*true*; x←X+1; y←Y-1
4: PC_4←*true*; x←X+1; y←Y-1 (x + y) >= 2
F
T
7: PC_7←(X+1)+(Y-1)<2
5: PC_5←(X+1)+(Y-1)≥2

(b) Symbolic Execution Tree

Figure 1.1: Symbolic Execution with Integer Inputs

```
1 public void strEx (String s2) {
2   String s1 = "B";
3   String s3 = s1.concat(s2);
4   if (s3.startsWith("BA")) {
5     // true branch
6   } else {
7     // false branch
8   }
9 }
```

(a) Method with string input


1: PC_1←*true*; s2←S_2, Σ = {A-Z}, k = 2
2: PC_2←*true*; s1←S_1, S_1←'B', concrete value
3: PC_3←*true*; s3←S_3, S_3←S_1.concat(S_2)
4: PC_4←*true*; s3.startsWith("BA")
F
T
7: PC_7←¬S_3.startsWith("BA")
5: PC_5←S_3.startsWith("BA")

(b) Symbolic Execution Tree

Figure 1.2: Symbolic Execution with String Input

1.1.2 Symbolic Expressions

When SE encounters *Domain Operations*, such as integer addition or string concatenation, it creates new *Symbolic Expressions* by applying those operations to symbolic variables or existing symbolic expressions. The program statement on line 2 of Figure 1.1a, (`x = x + 1`), results in the symbolic expression and assignment (x $\leftarrow X + 1$) shown in Figure 1.1b. String concatenation on line 3 of Figure 1.2a produces the symbolic expressions on line 3 of 1.2b.

1.1.3 Path Conditions

SE maintains a propositional symbolic formula known as the *Path Condition* (PC). The PC represents the constraints that must be satisfied to execute the path followed by SE. The PC is a conjunction of symbolic predicates, and initially set to *true*: $PC_n \leftarrow \mathit{true}$, where n is a program location. When evaluating a conditional statement, SE conjoins a symbolic predicate to the PC based on the conditional expression, branch taken and current symbolic state. Figure 1.1b shows the results of evaluating the statement `(if ((x + y) >= 2))` with ($\texttt{x} \leftarrow X + 1$) and ($\texttt{y} \leftarrow Y - 1$). The *true* branch PC is ($PC_5 \leftarrow \mathit{true} \wedge ((X+1)+(Y-1)) \geq 2)$) and the *false* branch PC is ($PC_7 \leftarrow \mathit{true} \wedge ((X + 1) + (Y - 1)) < 2)$). The initial *true* value is eliminated from the PC when it is simplified. The evaluation of the statement on line 4 of Figure 1.2a produces ($PC_5 \leftarrow S_3$.startsWith(“BA”)) and ($PC_7 \leftarrow \neg S_3$.startsWith(“BA”)) for *true* and *false*, respectively (where $\neg$ is the negation symbol).

1.1.4 Solving Integer Constraints

Once a PC is constructed, SE uses a *Constraint Solver*, or simply *Solver*, to determine:

- Whether a PC evaluates to *true* (the PC is *satisfiable*, or SAT) or *false* (the PC is *unsatisfiable*, or UNSAT). A PC is SAT if there is a solution that evaluates its formula to true, otherwise it is UNSAT. A SAT PC means that the path explored by SE is feasible (or reachable). Note that this type of analysis determines if constraints can be satisfied and does not necessarily find satisfiable assignments.

- If there are satisfiable assignments of variables in the PC that correspond to the concrete input values that execute that program path. This is the basis of test input generation using SE.

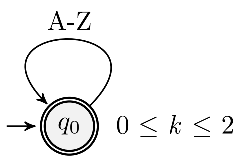
In order to produce a solution for the *true* branch (PC_5) in the example given in Figure 1.1, the solver must solve the inequality $((X + 1) + (Y - 1)) \geq 2)$ for the symbolic variables X and Y. For X, subtracting $(Y - 1)$ from both sides of the inequality yields $((X + 1) \geq 2 - (Y - 1))$. Since X was modified by a domain operation (addition), the solver performs the inverse operation (subtraction) in order to isolate X: $((X+1)-1 \geq 2-(Y-1)-1)$, which simplifies to $(X \geq 2-Y)$. If the inequalities for X and Y cannot be solved, the PC for that branch becomes UNSAT and the path is marked as infeasible, otherwise it is SAT. The inequalities in this example can be satisfied with $X = 1$, $Y = 1$. When using these values as inputs for `x` and `y`, the program executes the *true* branch.

Solving integer constraints systematically is possible because the inverses of integer operations are well defined. Addition and subtraction have an inverse relationship as do multiplication and division. Clearly, the algebra for solving integer inequalities is well established. However, the theory of strings is not as well developed and cannot guarantee for string operations to have inverses. Thus, making it difficult to design generic algorithms for solving string constraints.

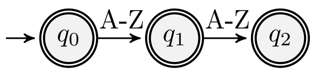
Before examining the problems related to automata-based string constraint solving, the automata-based string model is introduced.

1.1.5 Symbolic String Models

A *Symbolic String Model* (or simply *String Model*) is the construct used to model a set of strings. Since the number of possible values a symbolic string can take grows exponentially with length, storing these values as a set of concrete strings is not feasible. While Section 2.1 presents a detailed comparison of constructs used to model strings, two types of automata commonly used for this purpose are discussed here: *bounded* and *acyclic*. Figure 1.3 presents a comparison of bounded and acyclic automatons for a string $\Sigma = \{\text{A-Z}\}$, $0 \leq k \leq 2$. The bounded-automaton in Figure 1.3a is more compact, because it tracks the string length separate from the automaton. The acyclic-automata enforces string length by construction. Previous research on evaluating automata types for modeling strings in SE has shown that acyclic-automata reduce *over-approximation* (discussed in Section 1.4) in string operations [16]. Since accuracy is essential to the efficiency of test case generation, this work focuses on the acyclic-automata model. From this point on, references to automata assume acyclic-automata, and all references to string models assume acyclic-automata string models.

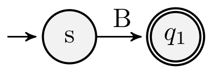


(a) Bounded Automata

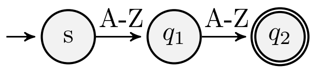


(b) Acyclic Automata

Figure 1.3: Bounded vs. Acyclic Automata, $\Sigma = \{\text{A-Z}\}$, $0 \leq k \leq 2$



(a) S_1: Concrete Value 'B'



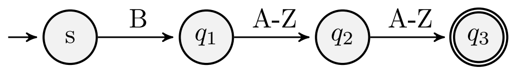
(b) S_2: $\Sigma = \{\text{A-Z}\}$, $k = 2$

Figure 1.4: Acyclic Automata for Concrete and Symbolic String Variables S_1, S_2

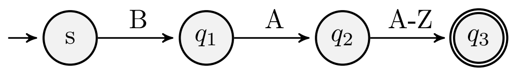
As further examples of acyclic models, Figure 1.4 shows acyclic-automata models for strings S_1 and S_2. Figure 1.4a shows S_1 with the single (or *concrete*) value "B". Figure 1.4b shows S_2 of length $(k) = 2$ and alphabet $(\Sigma) = \{$A-Z$\}$. The example shown in Figure 1.2 uses strings S_1 and S_2 as defined in Figure 1.4. The next subsection explains string operations.

1.1.6 Symbolic String Operations

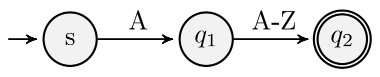
The example in Figure 1.2 includes concatenation of S_1 and S_2. Since S_1 and S_2 can represent more than one string value, the result of this operation is the cross product of the sets S_1 and S_2. For example, if strings *prefix* = {a, b} and *suffix* = {c, d}, *prefix*.concat(*suffix*) results in the strings {ac, ad, bc, bd}. Figure 1.5a shows the result of S_1.concat(S_2), which is assigned to S_3. It is important to note that while the automaton in Figure 1.5a represents all possible values of string S_3 at that location, the automaton cannot distinguish between the "B" and string S_2: it has aggregated the states and transitions. Next, SE encounters a conditional statement at line 4 and applies the predicate to determine the PC for each branch.



(a) S_3=S_1`.concat(`S_2`)`



(b) S_3`.startsWith("BA")`



(c) S_3`.startsWith("BA").substring(`S_1`.length())`

Figure 1.5: Removal of Concrete String from Concatenation Result

1.1.7 String Predicates

The predicate in the conditional statement at line 4 of Figure 1.2 is the Java string method `startsWith("BA")` applied to string S_3. Post-predicate string values for S_3 in the *true* branch all start with "BA", with all other pre-predicate string values executing the *false* branch. Figure 1.5b shows the automaton for S_3 on the *true* branch. Note that all possible values for S_3 on the *true* branch fail to execute the *true* branch if used as input values: The string "B" concatenated with strings that begin with "BA" results in strings that start with "BB", which execute the *false* branch instead.

1.1.8 Solving String Constraints

When SE determines a symbolic expression for a string, it performs the string operations to determine possible values of the program variable at that location. At conditional statements, SE applies the predicate to restrict these values and determine if a branch is feasible. If there are possible values, then the PC for that branch is UNSAT, which means that the branch cannot be executed on that path.

Even though SE generates possible values for strings taking a branch, those values cannot serve as inputs reaching that branch, because string operations applied to inputs modify their initial values. These string operations must be "undone," i.e., "inverted" in order to generate inputs from string values at the branch outcome.

1.1.9 Inverse String Operations

To generate values for S_2 that execute the *true* branch, the concatenation must be "undone" with *Inverse String Operations*. An inverse string operation has an inverse relationship with a corresponding string operation. For example, a string operation that inserts a character at an index can be "inverted" with one that deletes the character at that index. Inverse string operations may be defined in terms of existing string operations, as $+$ and $-$ for integers, or may require custom algorithms that modify the string model elements. This work assumes that all string operations of the string constraint solver are available for defining inverse string operations.

Note that when referring to a Java string method specifically, the term method is used. The text uses the term operations when it refers to a string operation on an automaton. The string operations model the Java string methods, and have corresponding inverse string operations.

In the example given in Figure 1.5, it is possible to define inverse concatenation using the Java string method `substring(int start)`, which returns the substring from index `start` to the end of the string. Since S_1 a concrete value, it has a single length which can be referenced with S_1`.length()`. Combining these methods yields $S_2 = S_3$`.substring(`S_1`.length())`. Figure 1.5c shows the result: an automaton that accepts strings of length 2 which start with "A". This auomaton accepts all strings that make `s2` successfully reach the *true* branch.

1.2 Motivating Example

In the previous string example, two factors facilitate the straightforward implementation of the inverse concatenation:

The solver can determine the length of S_1 - Since S_1 is concrete with a known length (1), the solver removes the correct number of characters from S_3 to find S_2.

The inverse operation is expressed in terms of an existing string operation - This eliminates the need to design new operations.

However, making minor changes to the previous string example significantly increases the complexity of the string constraint. Figure 1.6 presents this example, with the following modifications:

The concatenation arguments are both symbolic string inputs - The inputs (`s1`$\leftarrow S_1$), (`s2`$\leftarrow S_2$) are defined $\Sigma = \{$A-Z$\}$ and $1 \leq k \leq 2$. Now the solver must account for ranges of input lengths.

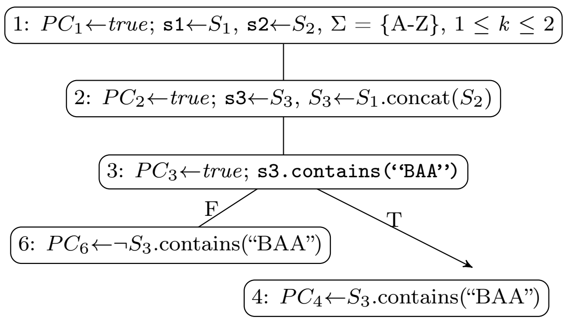
The predicate is now contains("BAA") - Applying this predicate to the concatenation result creates a complex automaton with several accepting paths.

The goal is to compute values for inputs `s1` and `s2` that reach the *true* branch of the conditional statement at line 3. The PC for this branch is $PC_4 \leftarrow S_3$.contains("BAA"). Figure 1.7 shows S_1 and S_2, each contributing either 1 or 2 characters to the concatenated result which is the automaton with length $2 \leq k \leq 4$ shown in Figure 1.7b.

Figure 1.7c shows the result of applying predicate `contains("BAA")`. Since a minimum of 3 characters in a string are required to make the predicate evaluate

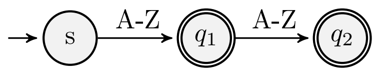
```java
public void strEx (String s1, String s2) {
  String s3 = s1.concat(s2);
  if (s3.contains("BAA")) {
    // true branch
  } else {
    // false branch
  }
}
```

(a) Method with string inputs

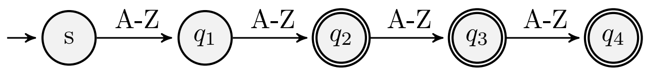

1: $PC_1 \leftarrow true$; s1←S_1, s2←S_2, $\Sigma = \{$A-Z$\}$, $1 \le k \le 2$
2: $PC_2 \leftarrow true$; s3←S_3, $S_3 \leftarrow S_1$.concat(S_2)
3: $PC_3 \leftarrow true$; s3.contains("BAA")
F
T
6: $PC_6 \leftarrow \neg S_3$.contains("BAA")
4: $PC_4 \leftarrow S_3$.contains("BAA")

(b) Symbolic Execution Tree

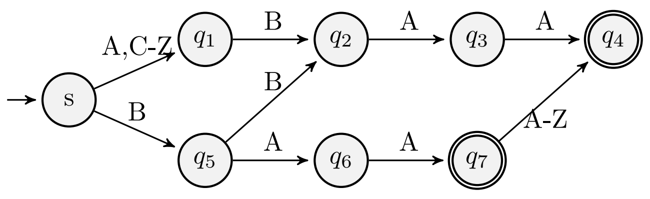
Figure 1.6: Motivating Example, Concatenation of Symbolic Strings



(a) S_1, S_2: $\Sigma = \{$A-Z$\}$, $1 \le k \le 2$



(b) S_3=S_1.concat(S_2)



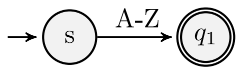
(c) S_3.contains("BAA")

Figure 1.7: Concatenation of Symbolic Strings and Application of Predicate

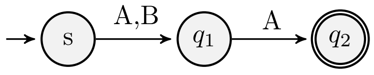
to *true*, the result has a range of lengths: $3 \le k \le 4$. In this example, designing an inverse conatenation is complicated by the following factors:

S_1 and S_2 represent strings of various lengths - The inverse concatenation needs to account for 4 combinations of lengths of S_1 and S_2: (S_1: $k = 1$, S_2: $k = 1$), (S_1: $k = 1$, S_2: $k = 2$), (S_1: $k = 2$, S_2: $k = 1$), (S_1: $k = 2$, S_2: $k = 2$).

Using substring operation as inverse for concat introduces spurious strings - The substring operation in the previous example produces a solution containing only strings that execute the target path. An over-approximating inverse operation introduces *Spurious strings* that do not execute the desired path. Using the substring operation as before with the same lengths (S_1: $k = 1$, S_2: $k = 2$) results in spurious strings. In this case both the starting and ending indexes of the desired substrings are specified: ($S_1 = S_3$.contains("BAA").substring(0,1)) and ($S_2 = S_3$.contains("BAA").substring(1,3)). The result for S_1 in Figure 1.8a accepts "A" and the result for S_2 in Figure 1.8b accepts "AA". However, using s_1 = "A", s_2 = "AA" does not execute the desired path. While this solution does contain the single correct result for lengths (S_1: $k = 1$, S_2: $k = 2$), (s_1 = "B" and s_2 = "AA"), it also contains 51 spurious combinations.



(a) $S_1 = S_3$.contains("BAA").substring(0,1)



(b) $S_2 = S_3$.contains("BAA").substring(1,3)

Figure 1.8: Attempting to Determine S_1, S_2 with Substring Operation

The resulting automaton lost information about S_1 and S_2 - Due to inability to determine which states and transitions correspond to each target and argument, programming a new precise inverse operation to separate them is difficult.

S_1 and S_2 are dependent - The concatenation of S_1 and S_2 introduces dependencies between their values in that choosing a test input value for one may affect valid choices for the other. Choosing values for independent variables can be done without regard for other variables.

1.3 Challenges

These specific problems of generating test inputs for string manipulating programs can be categorized into the following challenges.

Modeling Inverse String Operations - Some inverse string operations can be defined in terms of existing automata string operations. An example of an inverse relationship between Java methods are `insert(int offset, char c)` and `delete(int start, int end)`. In this case, the delete method can be used as the inverse of the insert method. Since the solver knows the length (1) and the position (`offset`) of the inserted element, it can call `delete(offset, (offset + 1))` to invert the insert operation. However, the method `insert(int offset, String str)` cannot be modeled with existing operations. If the argument *str* represents a single string value, such as "AB", then the length can be determined and we can model the inverse operation with `delete(int start, int end)`. This is because we know about the position and length of the argument. If the argument *str* is not concrete, but instead represents string values of more than one length, this naive approach fails. Thus, new inverse operations should be provided.

Handling Non-Injective Functions - Some string operations are *non-injective*, meaning they do not have a 1:1 relationship between each input and output. An example of a non-injective function is the method `delete(int start, int end)`. To invert the delete operation, the solver can determine the location and length of the deleted characters, but cannot determine what was deleted. Performing the delete operation on multiple unique strings may produce the same output, hence making it impossible to determine the relation between the result and the original strings of the delete operation.

Maintaining Dependencies and Relationships - Reaching a given point during execution may depend on the values and relationships of multiple variables. All of them must be solved and relationships between the values maintained. An input can be used in different locations, or be related to itself such as a string being concatenated with itself.

Before presenting the thesis statement, it is important to define solver characteristics and how they contextualize computed solutions.

1.4 Solver Characteristics

A *sound* constraint solver does not report a PC is UNSAT when it is SAT. In other words, if a PC has a solution, a sound solver finds it, i.e., it does not report any false negatives. However, a sound solver may report an UNSAT PC as being SAT, termed a false positive, due to *Over-approximation* of the solution set in order to make operations closed. Over-approximation occurs when a solution contains all concrete values that satisfy a PC, as well as some that do not.

A *complete* solver never reports an UNSAT PC as SAT. In other words, if a PC has no solution, a complete solver never reports one. It can also be said that a complete solver never reports false positives. However, a complete solver may miss a solution and report a SAT PC as UNSAT, a false negative. This is *Under-approximation*, which occurs when a solution contains only values that satisfy a PC but contains a subset of all such values.

Some amount of over-approximation (false positives) can be tolerated, and some string constraint solvers allow for over-approximation in order to ensure a sound solution [19]. These approaches may produce a solution such as the one presented in Figure 1.8 since it does produce the valid combination of inputs for the chosen lengths (S_1 = "B", S_2 = "AA"). However, that is the only valid combination out of the 52 possible, which is a considerable number of false positives.

In general, it is impossible for a solver to be both sound and complete for undecidable problems such as the satisfiability of a string PC [3]. The focus of this work is to demonstrate practical methods that can produce sound and complete solutions within certain contexts, such as within the length of input strings.

1.5 Thesis Statement

A complete test input generator for Java string programs can be implemented using symbolic execution with an acyclic-automata based string constraint solver that accurately models inverse string operations and ensures consistency between dependent solutions.

This work aims to address the following research questions that support this statement:

- **RQ1** *Can all inverse string operations be accurately modeled?* In answering this question we investigate over-approximation and the use of existing string operations, as well as methods for implementing those that cannot be modeled with existing string operations.

- **RQ2** *How to maintain the dependencies while solving for inputs?* Since single-track automata cannot model relationships between strings, we investigate techniques to maintain these relationships.

- **RQ3** *Is the solution practical and effective?* We evaluate whether the methods can be used with real-world programs and their effectiveness at finding test inputs.

This rest of this thesis is organized as follows:

Section 2 introduces string models, constraints and solvers. It provides an overview of current solvers and contrasts them with the proposed solver.

Section 3 presents the backward analysis algorithms. It details the inverse string operations and how the different node types are evaluated. This section answers the first two research questions on modeling inverse string operations and handling dependencies.

Section 4 Details implementation of the proposed solver, inverse string operations and its integration with Symbolic Pathfinder.

Section 5 presents empirical evaluations of this inverse solver framework and provides answers to the last research question on practicality and effectiveness.

Section 6 concludes this thesis by summarizing the findings and proposing future research that focuses on the efficiency of this framework.

SECTION 2

BACKGROUND AND RELATED WORK

2.1 String Models

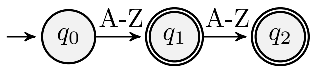
A string is a finite sequence of symbols, chosen from a finite set of symbols (*alphabet*, Σ), with a non-negative length ($k \in \mathbb{N}^0$). A string with length $k = 0$ is the *empty string* (ε). String models represent the set of possible strings a string variable may take. As discussed in Section 1.1.5, the size of a string set grows exponentially with length, making it infeasible to represent it explicitly as a set of concrete strings. To mitigate this issue, a different representation is required that encodes a set of strings efficiently and updates its structure without undue computational cost.

A Finite State Automata (FSA) meets such requirements. An FSA is a state-transisitional system where transitions (edges) are labeled with a symbol from the alphabet Σ. A path in an FSA represents a sequence of symbols, i.e., a string. The formal definition for deterministic finite state automata, a type of FSA, is the quintuple (Q, Σ, E, q_0, F) where:

- Q is a finite set of states, $Q \neq \emptyset$

- Σ is a finite set of symbols called the *alphabet*, $\Sigma \neq \emptyset$
- E is the set of edges, $E : (q, c, p) | q, p \in Q, c \in \Sigma$
- q_0 is the start state, $q_0 \in Q$
- F is the set of accepting states, $F \subseteq Q$

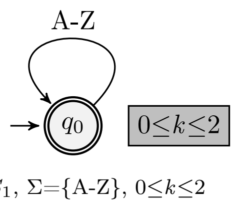
The language $\mathcal{L}$ of an FSA $\mathcal{A}$ is the set of strings accepted by the FSA, $\mathcal{L}(\mathcal{A})$. A string is accepted if there exists a path in $\mathcal{A}$ from the starte state q_0 to an accepting state. Figure 2.1 gives an example of a simple FSA that encodes strings of lengths one and two over the alphabet A-Z. This work uses the word automaton to reference FSA.



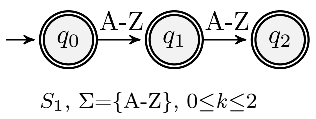
Σ={A-Z}, $1 \leq k \leq 2$

Figure 2.1: Simple Finite State Automata

Various types of automata are used to model strings. A majority of research on automata-based string models manipulate *unbounded-automata* [4,9,18,20–22]. Unbounded-automata are space efficient because they contain *cycles*, i.e., when a state can have a path to itself. This allows an unbounded-automaton with finite states to represent infinitely many strings. Unbounded-automata do not encode information about length, so there is no inherent mechanism to prevent endless traversal of a cycle, which test case generation requires for better precision. In order to represent strings of finite length, i.e., to create bounded-automata, a separate mechanism to enforce bounds is added to the unbounded model. Figure 2.2a presents a bounded-automaton for string S_1, Σ=\{A-Z\}, $0 \leq k \leq 2$. This automaton requires only one state and transition, with the length tracked separately.



(a) Bounded-Automata

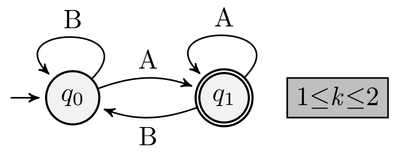


(b) Acyclic-Automata

Figure 2.2: Bounded vs. Acyclic-Automata

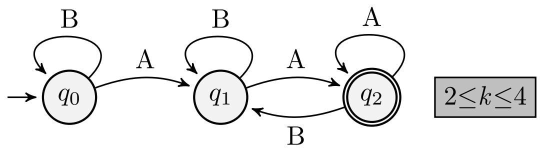
In contrast to the bounded-automata, *acyclic-automata* do not contain cycles, and maintain bounds on length internally. Acyclic-automata are not as space efficient as bounded-automata, as Figure 2.2b shows the acyclic-automaton for string S_1 requires three states and two transitions. Since an acyclic-automaton has no cycles and a finite number of states, its language is finite.

Another consideration is that applying a string operation to a bounded-automata string model can lead to over-approximation. This is due to the fact that the bounded-automata does not encode length internally [8,16]. Figure 2.3 presents an example from [8] when bounded-automata over-approximates operations. Figure 2.3a shows the unbounded-automaton for strings S_1, S_2, Σ=\{A-Z\}, $1 \leq k \leq 2$. Then, after concatenate(S_1, S_2), a new automaton is produced as shown in Figure 2.3b. Since the possible values for S_1 and S_2 are {`A, AA, BA`}, the concatenate operation should result in the values {`AA, AAA, ABA, BAA, AAAA, AABA, BAAA, BABA`}. However, the bounded-automaton in Figure 2.3b accepts the additional values {`ABAA, ABBA, BBAA`}. This over-approximation is caused by the lack of length information in the bounded-automata. In contrast, the example in Figure 2.4 of acyclic-automata concatenation from [8] shows that a larger acyclic-automaton accepts the correct strings {`AA, AAA, ABA, BAA, AAAA, AABA, BAAA, BABA`}.



S_1, S_2: Σ={A-Z}, $1 \le k \le 2$, values={`A`,`AA`,`BA`}

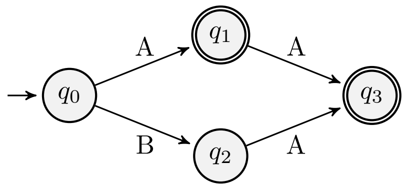
(a) Unbounded-Automata S_1, S_2



result: Σ={A-Z}, $2 \le k \le 4$, values={`A`,`AAA`,`ABA`,`BAA`,`AAAA`,`AABA`,`BAAA`,`BABA`,`ABAA`,`ABBA`,`BBAA`}

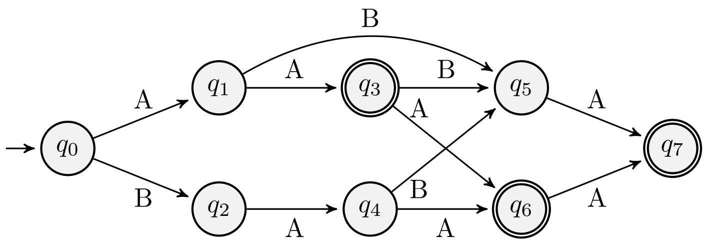
(b) Unbounded-Automaton Concatenate (S_1, S_2)

Figure 2.3: Over-Approximation with Unbounded-Automata



S_1, S_2: Σ={A-Z}, $1 \le k \le 2$, values={`A`,`AA`,`BA`}

(a) Acyclic-Automata S_1, S_2



result: Σ={A-Z}, $2 \le k \le 4$, values={`AA`,`AAA`,`ABA`,`BAA`,`AAAA`,`AABA`,`BAAA`,`BABA`}

(b) Acyclic-Automata Concatenate (S_1, S_2)

Figure 2.4: Avoiding Over-Approximation with Acyclic-Automata

Several works of Bultan et al. [18,19] use *multi-track automata* to model sets of strings. In particular, STRANGER [20] represents symbolic strings as multi-track automata implemented as Multi-terminal Binary Decision Diagrams [6] (MTBDD) using MONA [13]. Other examined works employ fixed-size, ordered, lists of bits called *bit-vectors* [11, 14, 23] to encode strings, and research indicates bit-vector string models demonstrate performance advantages compared to automata string models [15]. This work focuses on simple, single track automata as a method for representing strings.

2.2 Solvers

Advances in research on string constraints resulted in addtional string constraint solvers supporting diverse analyses. While a comprehensive examination of all available solvers is outside the scope of this thesis, Table 2.1 presents popular string constraint solvers and relevant to this work properties. The *Model* column describes the type of string model used: automata, bit-vector, or if the solver is axiom-based. The *Type* column contains the supported constraint types, where *mixed* indicates that the solver supports a wider range of constraints than the combination of string and integer constraints. The *Semantics* column contains the language whose string operation semantics the solver implements. The *Application* column presents the targeted task used in the solver evaluation.

Table 2.1: Popular String Constraint Solvers

Solver	**Model**	**Type**	**Semantics**	**Applications**
Z3-str, Z3 [23]	axiom-based	mixed	SMT-LIB	general mixed-constraint
STRANGER [20, 22]	automata	String	PHP	vulnerability detection
Redelinghuys et.al. [15]	automata and bit-vector	String, Int	Java	model comparisons, verification
JST [4]	automata	String, Int	Java	input generation, verification
HAMPI [11]	bit-vector	String	Web, C	vulnerability, bug finding
CVCS4 [14]	bit-vector	mixed	SMT-Like	general mixed-constraint

The work presented by Redelinghuys et al. [15] compares automata and bit-vector based symbolic string models. While the work focuses on this comparison, it provides insights into the relative merit of the two most widely used types of string models.

The string constraint solver Z3-str [23] implements semantics of the SMT-LIB [2] string theory, which might differ from semantics of a particular programming language. This solver is integrated into the *Satisfiability Modulo Theory* (SMT) solver Z3. SMT solvers convert a formula in a particular theory into Boolean satisfiability formula that are then passed to a satisfiability (SAT) solver. SMT solvers handle mixed-constraints by first solving constraints in one theory and then substituting these solutions for variables in constraints for another theory. This process continues until all solvers compute solutions consistent with each other.

CVCS4 [14] is a mixed-constraint SMT solver. However, unlike other SMT solvers, it incorporates techniques for solving string constraints that do not rely upon reduction to satisfiability problems.

HAMPI [11] operates on string constraints that express membership in regular and fixed-size context-free languages. It converts these constraints into bit-vector logic, which is then passed to a solver that supports bit-vector theory. In this regard, HAMPI acts as a pre-processor for other solvers.

Designed for vulnerability detection in PHP code, STRANGER [20] performs forward and backward data-flow analysis with automata over control-flow graphs. STRANGER uses a fixed-point solving algorithm that includes widening operations in order to ensure convergence.

Although similar to the solver presented in this work in most respects, JST [4] computes solutions to both integer and string constraints. It solves mixed constraints in a manner similar to SMT solvers.

Both JST [4] and STRANGER [20,22] are most similar to the solver presented in this work, since they are all automata-based solvers.

2.3 Constraint Solving

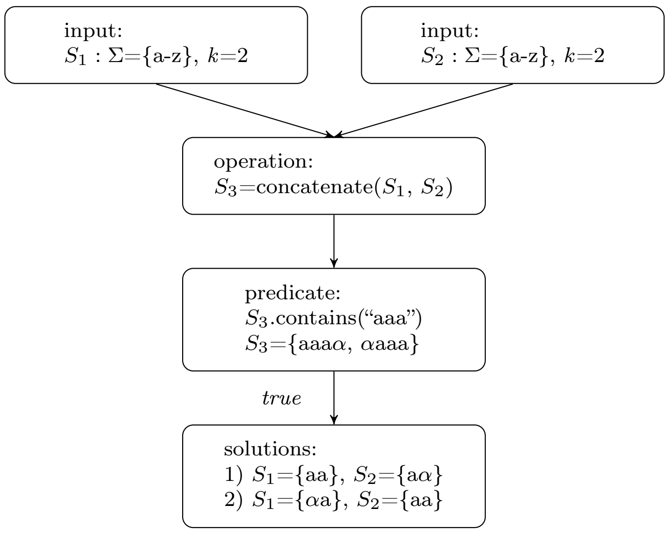
Now we analyze how these related solvers approach solving string constraints.

JST handles mixed constraints of types integer and string. The integer constraints are solved first to obtain concrete integer values that are used in solving string constraints. If no solution can be found for the string constraints, another solution to the integer constraints is generated and the process continues. The solver presented in this work assumes that concrete values are already present in string constraints. While JST uses the same automata library as the solver presented here, `dk.brics.automata` [4], it uses unbounded instead of acyclic-automata models. The authors recognize that over-approximation can occur in the existing string operations, and indicate that some functions require extra handling [4]. However, it is not apparent that over-approximation is addressed.

Bultan et al. provide a body of work on string analysis [1, 3, 18–22], including the string constraint solver STRANGER. STRANGER uses fixed-point calculations to analyze programs using data-flow frameworks. At the start of backwards analysis, an initial work item (automaton) representing the target location (predicate constraint) is placed in a queue. Work items are removed from the queue and pre-string operation automata are computed (similar to inverse string operation in this work). These represent incoming flow values for other work items in the control-flow graph of the program. If the values are different from previously solved incoming flows, then the related work items are updated and placed in the queue. The queue is processed until it is empty, at which point no new incoming flow values are being generated and a fixed-point computation has been achieved. In contrast, the proposed solver analyzes string constraints on a single path in the programs control-flow graph. Details of this proposed framework are presented in the next section.

In their other work [19], the authors examine vulnerability analysis using an automata-based solver. Because in that application avoiding over-approximation is not a primary concern, over-approximation is traded for a sound solution. In the context of vulnerability analysis, a sound solution including all vulnerable inputs but with some false-positives is preferable to a solution missing vulnerable inputs but having no false-positives. As a result, the algorithms for computing pre-string operation values in the previous work are not as precise as the ones implemented in this solver.

Relational Constraints


input:
S_1 : Σ={a-z}, k=2
input:
S_2 : Σ={a-z}, k=2
operation:
S_3=concatenate(S_1, S_2)
predicate:
S_3.contains("aaa")
S_3={aaaα, αaaa}
true
solutions:
1) S_1={aa}, S_2={aα}
2) S_1={αa}, S_2={aa}
Figure 2.5: Related Inputs

To further improve precision, the solver should maintain relations between certain values. A primary characteristic of this solver is the ability to handle relationships between inputs formed by string operations. Figure 2.5 provides an example of related inputs resulting from the concatenation of symbolic strings S_1, S_2: Σ={a-z}, k=2. Solutions for the predicate S_3.contains(“aaa”) = *true* are given, with $\alpha \in \Sigma$. Due to the bound on length, (k=2), each input string contributes either one or two characters to the post-predicate values of {aaaα, αaaa}. Possible values for S_1={aa, αa} and S_2={aα, aa}. If input values are chosen for S_1 and S_2 without regard for the relationship between them, a great number of the resulting combinations do not reach the correct branch.

F. Yu et al. [18] compute solutions for related inputs with the use of memory-intensive, computationally complex *multi-track automata.* This type of automata encodes related values, such as the possible values for the prefix and suffix of a concatenation operation. In contrast, this proposed solver implements an approach of iteratively propagating concrete values for related inputs. The next section presents details of the proposed approach.

SECTION 3

APPROACH

The key elements for successfully implementing the proposed solver are the backward analysis and inverse string operations algorithms. The general approach to performing the backward analysis is to create a *transposed constraint graph* (TCG) in which the nodes contain a majority of the required functionality. Essentially the backward analysis traverses the TCG. The basic approach is to compute and propagate incoming and outgoing values at each node, and traverse the TCG with the help of the evaluation stack.

The implementations of inverse string operations depend on the type of the operation. The most straightforward approach is for those inverse operations that return sound and complete results. For inverse operations that return sound but incomplete results, the solver eliminates the incompleteness. Finally, inverse operations that deal with related inputs rely on the framework algorithm for soundness.

The answer to two research questions introduced in Section 1.5 guides the presentation of this section:

RQ1 *Can all inverse string operations be accurately modeled?* Section 3.2.1

provides formal definitions for the inverse string operations that positively answer this question. To help with answering RQ1, we partitioned it into a series of the following questions:

Does over-approximation occur in an inverse operation and if so then how is it mitigated? Section 3.1.7 presents the over-approximating inverse operations and the solution to handling such over-approximations.

Can existing string operations be used to model inverse operations? Section 3.2.1 provides examples of inverse string operations modeled with existing string operations such as `insert(int index, String arg)`$^{-1}$ and `reverse()`$^{-1}$.

How to define inverse operations that cannot be expressed with existing automata operations? Operations such as `toLowerCase()`$^{-1}$ cannot be defined in terms of existing string operations. Directly modifying the automata that encodes the string values provides a way to implement these inverse functions. Section 3.1.7 describes such modifications.

RQ2 *How to maintain dependencies between string values while solving string constraints for solutions?* Section 3.1.8 explains how related data-flow values are determined and propogated in a way that maintains their relationships.

The following Section 3.1 details the backward analysis in a presence of unsound, but complete inverse operations. After that Section 3.2 focuses on inverse operations.

3.1 Backward Analysis

3.1.1 Constraint Graph

Before the backward analysis begins, the solver performs the forward analysis on a string constraint graph that encodes string constraints: its nodes are expressions and edges data-flow of string values between them. Figure 3.1 presents an example constraint graph, where nodes are string inputs (node 5), operations (nodes 10 and 17), predicates (node 32) and concrete strings (node 30).

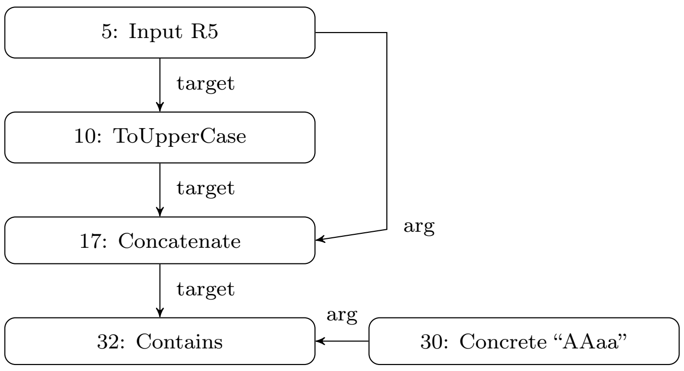


Figure 3.1: Constraint Graph

Directed labeled edges specify type of data uses, which can be either *target* or *argument* for the destination node. In object-oriented terms, the target is the string object (automaton) on which the instance method (string operation) is called. Nodes in the constraint graph can have multiple incoming and outgoing edges. Each outgoing edge indicates a use of the node's outgoing value. Each node contains a numerical identifier (node ID) indicating an order for evaluating nodes during forward analysis. The forward analysis traverses the constraint graph in total-order on node ID until it determines the possible string values at a predicate node and evaluates it to *true* or *false*.

3.1.2 Transposed Constraint Graph

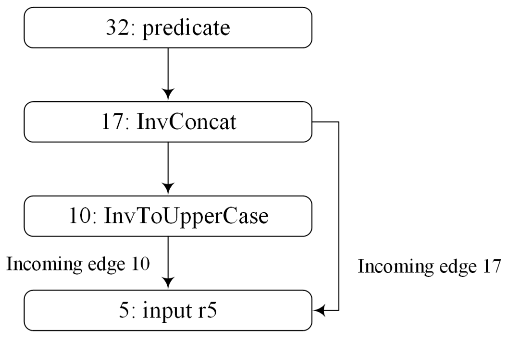


Figure 3.2: Transposed Constraint Graph

Backward analysis starts after forward analysis completes the evaluation of a predicate node. The framework builds a TCG, consisting of *inverse constraint nodes*, while reversing (or transposing) edge directions from the constraint graph. In a TCG, a node may have multiple incoming edges representing multiple uses of a value. Figure 3.2 shows the TCG of the constraint graph in Figure 3.1. Note that "input r5" has multiple incoming edges since it is the target of the toUpperCase() string operation as well as the argument to the concat() string operation in the constraint graph. In order to find a solution for input r5, the values of all the incoming edges must have a common element. Each inverse node contains a *solution set* that keeps a set of solutions from each incoming edge. A solution set is said to be *consistent* when the intersection of all its elements is not empty. Figure 3.3 shows a diagram of an inverse constraint node and its solution set.

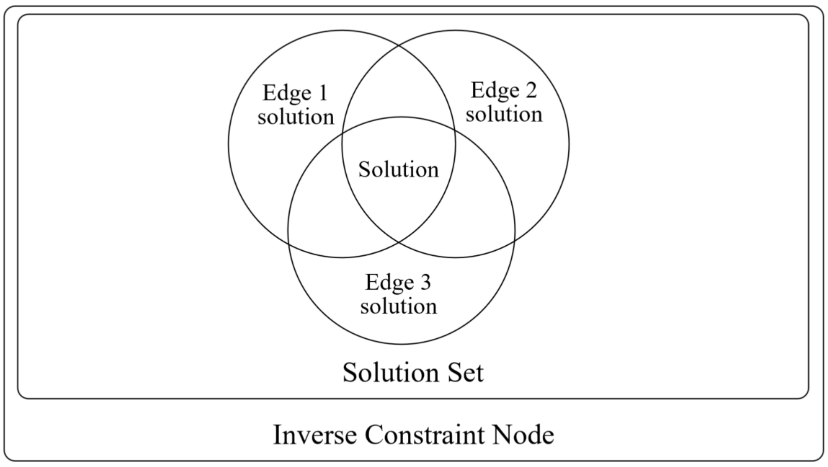


Figure 3.3: Inverse Node with Solution Set

3.1.3 Graph Traversal

Backward analysis starts at the post-predicate values and propagates their results toward the input nodes by performing a depth-first traversal of the TCG. The solver maintains a stack of nodes to be evaluated, and initializes it with the predicate. Here, the evaluation stack is an abstract concept and can be implemented as either an actual stack or as a series of function calls in which each node calls the `evaluate(`*inputNode*`,` *sourceIndex*`)` function on the next inverse constraint node in the TCG. The algorithms presented here use the latter.

Algorithm

Algorithm 1 depicts a pseudocode for the traversal algorithm in which each node calls the `evaluate(`*inputNode*`,` *sourceIndex*`)` method on the next (target) node in the TCG. Below are the assumptions that Algorithm 1 relies on:

- Each node in the TCG has references to its children and parents.

- Each incoming edge represents a use of the node output in the original constraint graph.
- Each node has access to the results of the forward analysis.

The algorithm takes as input a predicate node p of the TCG. Each node's evaluate method takes two arguments: a reference to the calling node (the predecessor of the called node) and an integer that indicates which output to take from the calling node. Some nodes, such as those that handle related values, have multiple outputs. In the case of a predicate node, there is no predecessor and the input will be the output of the next node. The algorithm sets $inputNode$ and $sourceIndex$ accordingly and begins the traversal by calling `evaluate(`$inputNode$`, `$sourceIndex$`)` on the predicate node. If the returned value is false, then the solver has failed to find a solution, or the predicate was UNSAT.

Algorithm 1 Traverse Function

```
1: function TRAVERSE(predicate $p$)
2:     $inputNode \leftarrow$ null
3:     $sourceIndex \leftarrow 0$
4:     $solved \leftarrow p$.evaluate($inputNode$, $sourceIndex$)
5:     if not $solved$ then
6:         ▷ Unable to find solution
7:     end if
8: end function
```

3.1.4 Fallback Sequence

A fallback sequence begins when the evaluate function of a node returns false. Once initiated, a fallback sequence continues until:

A node has more values to propagate - Since unsound nodes propagate a subset of incoming values, it is possible that other unexplored values could lead to a consistent solution.

A predicate is reached - This serves as a check for defects. If a predicate has satisfiable assignments after the forward analysis, then there are corresponding inputs for those assignments. If the `evaluate(`*inputNode*`,` *sourceIndex*`)` call in a predicate returns false, then the solver has failed to find those inputs.

3.1.5 Node Evaluation

Each node calls the `evaluate(`*inputNode*`,` *sourceIndex*`)` functon on the next node in the TCG. The function is different for each node type. The node types are:

- Predicate Node
- Input Node
- Inverse String Operation Node - Operation that is Sound and Complete
- Inverse String Operation Node - Operation that Over-Approximates (Sound but Incomplete)
- Inverse String Operation Node - Relational String Operation (Unsound but Complete)

Predicate node evaluation propagates the post-predicate values and calls `evaluate(`*inputNode*`,` *sourceIndex*`)` to the next node. Since all arguments to a predicate are concrete, there is only one node following a predicate, i.e., the "target". Algorithm 2 presents the pseudocode for evaluating predicate nodes. The forward results of the next node are retrieved on line 2. If the results contain values, they are placed in the output set on line 4. The output set contains one or more sets of values for subsequent nodes to use as input. The algorithm then calls `evaluate(`*inputNode*`,` *sourceIndex*`)` on the next node in the TCG and returns the boolean result.

Algorithm 2 Evaluate Function for Predicate Nodes

```
   ▷ Each node has a pointer to $targetNode$
   ▷ Each node exposes an $outputMap$
1: function EVALUATE($inputNode$, $sourceIndex$)
2:     $resultModel$ ← $targetNode$.getModel()
3:     if not $resultModel$.isEmpty() then
4:         $outputMap$.put(1,$resultModel$)
5:         return $targetNode$.evaluate($thisNode$, 1)
6:     end if
7:     return false ▷ Error, predicate was UNSAT
8: end function
```

Since a node may have more than one parent, a construct is needed to keep all of the inputs from these calling nodes and determine if they are *consistent*. Each node has a solution set for this purpose, and it is said to be consistent if the intersection of all inputs in the set is not empty. The `evaluate(`*inputNode*`,` *sourceIndex*`)` function for input nodes demonstrates use of the solution set. Algorithm 3 presents the pseudocode for evaluating input nodes. The solution (input) from the calling node is retrieved on line 2. It is placed into a solution set on line 3. The solution set is checked for consistency on line 4 and if the solution set is not consistent the solution is removed on line 5 and a fallback is initiated on line 6 by returning false. If the solution set is consistent, the function returns true, as an input node has no child nodes (i.e., no next node to evaluate).

Algorithm 3 Evaluate Function for Input Nodes

```
    ▷ Each node has a pointer to $targetNode$
    ▷ Each node has an internal $solutionSet$
1: function EVALUATE($incomingNode$, $sourceIndex$)
2:     $solution \leftarrow incomingNode$.outputMap($sourceIndex$)
3:     $solutionSet$.setSolution($incomingNode$.getID(), $solution$)
4:     if (not $solutionSet$.isConsistent()) then
5:         $solutionSet$.remove($incomingNode$.getID()
6:         return false ▷ fallback to find new solutions
7:     end if
8:     return true
9: end function
```

Figure 3.4 presents an example of computing the solution for input "r5" from the TCG shown in Figure 3.2.

The algorithm starts with a predicate, 32, which has the value satisfying it `"AAaa"`. String values generated by each inverse operation are shown in each node. As solutions are added to the solution set of r5, they are intersected with all existing solutions in the solution set. If the intersection does not contain any values, a fallback sequence is started in an attempt to find new solutions. A solution is found for r5 once all incoming edges have been evaluated and the solution set is consistent. All incoming edges for all input nodes are considered evaluated once the series of evaluate calls completes. In this case, the solution is the intersection of incoming edge 10 and 17, which is `"aa"`. Using `"aa"` as the value input r5 in the constraint graph in Figure 3.1 shows that the *true* branch is taken, and the solution is correct.

The algorithm relies on correct implementation of inverse operations, which are detailed in the next section.

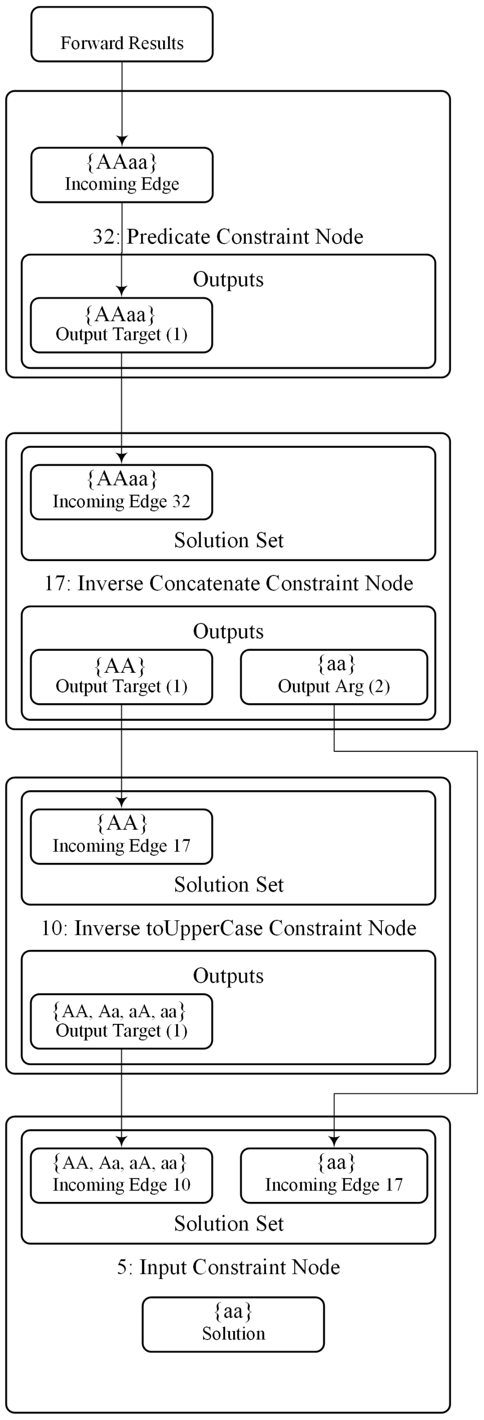


Figure 3.4: Input Nodes and Solution Sets

3.1.6 Sound and Complete Operations

String operations can be either injective or non-injective. Non-injective operations map more than one input to the same output. Injective operations map a single input to an output. In situations where the solver has sufficient information about an injective string operation, a sound and complete inverse result can be computed.

Algorithm 4 presents the pseudocode for the `evaluate(`*inputNode*`,` *sourceIndex*`)` for sound and complete nodes. The input is retrieved from the calling node on line 2. The inverse operation is applied on line 3. Lines 4-8 add the results to the solution set and check for consistency, returning false if the solution set is not consistent. If the solution set is consistent, lines 9-10 add the solution to the output set and call `evaluate(`*inputNode*`,` *sourceIndex*`)` on the next node.

Algorithm 4 Evaluate for Sound and Complete Inverse Operations

```
    ▷ Each node has a pointer to targetNode
    ▷ Each node exposes an outputMap
    ▷ Each node has an internal solutionSet
 1: function EVALUATE(inputNode, sourceIndex)
 2:     incoming ← inputNode.outputSet(sourceIndex)
 3:     solution ← inverseOperation(incoming)
 4:     solutionSet.setSolution(inputNode.getID(), solution)
 5:     if (not solutionSet.isConsistent()) then
 6:         solutionSet.remove(inputNode.getID())
 7:         return false ▷ fallback to find new solutions
 8:     end if
 9:     outputMap.put(1,solution)
10:     return targetNode.evaluate(thisNode, 1)
11: end function
```

To illustrate the algorithm, consider Figure 3.5 that shows the flow of a symbolic string through a forward string operation, predicate, and backward analysis with a sound and complete inverse string operation. In this example the string operation is insert(int offset, char c): S`.insert(1,‘a’)`. The predicate is S`.contains("bab")`. String S is defined with parameters k=2 and Σ={a,b}. The edges are labeled with the values for S. The inverse string operation is S`.invInsert(1,1)`, which deletes a single character at index one. The result is the single value `"bb"`, which is both sound and complete. In this case the solver has sufficient information (length and position) to remove the inserted character sequence to compute an accurate result. In this context, the insert operation is injective, as there is only one possible input value, `"bb"`, that results in the output value `"bab"`.

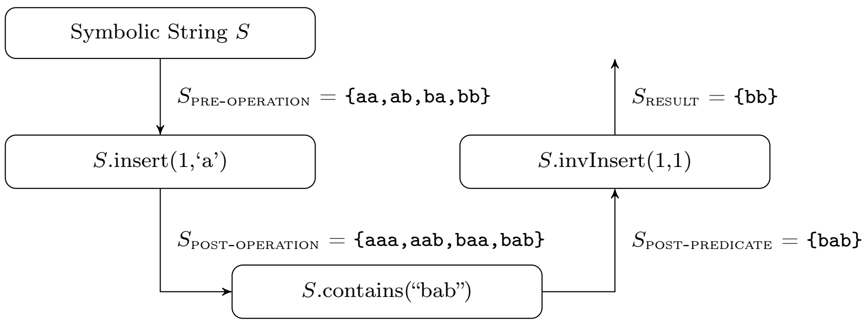

Symbolic String S
$S_{\text{PRE-OPERATION}}$ = {aa,ab,ba,bb}
S.insert(1,‘a’)
$S_{\text{POST-OPERATION}}$ = {aaa,aab,baa,bab}
S.contains(“bab”)
$S_{\text{POST-PREDICATE}}$ = {bab}
S.invInsert(1,1)
S_{RESULT} = {bb}

Figure 3.5: Sound and Complete Inverse Operation

3.1.7 Handling Over-Approximation

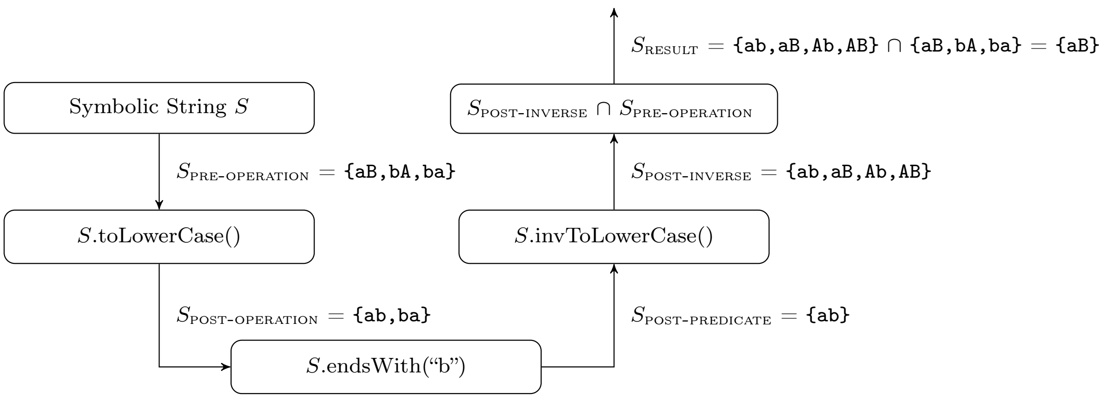
A non-injective string operation results in unavoidable over-approximation in its inverse string operation. A common approach for eliminating over-approximation is to intersect the over-approximated result with the results of the forward analysis [21]. This step removes the spurious strings introduced by the over-approximating inverse.

The `evaluate(`*inputNode*`,` *sourceIndex*`)` function for a node with an over-approximating inverse string operation performs the intersection required to eliminate the over-approximation. Algorithm 5 presents the pseudocode for such a function, with the intersection occurring on line 4.

Algorithm 5 Evaluate for Over-Approximating Inverse Operations

```
    ▷ Each node has a pointer to targetNode
    ▷ Each node exposes an outputMap
    ▷ Each node has an internal solutionSet
 1: function EVALUATE(inputNode, sourceIndex)
 2:     incoming ← inputNode.outputSet(sourceIndex)
 3:     solution ← inverseOperation(incoming)
 4:     solution ← intersect(solution, targetNode.forwardResult)
 5:     if solution.isEmpty() then
 6:         return false ▷ fallback to find new solutions
 7:     end if
 8:     solutionSet.setSolution(inputNode.getID(), solution)
 9:     if (not solutionSet.isConsistent()) then
10:         solutionSet.remove(inputNode.getID())
11:         return false ▷ fallback to find new solutions
12:     end if
13:     outputMap.put(1,solution)
14:     return targetNode.evaluate(thisNode, 1)
15: end function
```

Figure 3.6 gives an example of the non-injective string function `toLowerCase()` and the subsequent over-approximation in `invToLowerCase()`. Given a string S, Σ={a, b, A, B}, k=2, which has the initial values {`aB, bA, ba`}, the `toLowerCase()` function produces $S_{\text{POST-OPERATION}}$ = {`ab, ba`}. Application of the predicate produces $S_{\text{POST-PREDICATE}}$ = `{ab}`, which is input to the `invToLowerCase()` operation. However, the lower case string `"ab"` is the result of calling `toLowerCase()` on any of the strings {`ab, aB, Ab, AB`}, with only one of the four present in $S_{\text{PRE-OPERATION}}$. Intersecting $S_{\text{PRE-OPERATION}}$ with $S_{\text{POST-INVERSE}}$ eliminates the additional strings introduced by `invToLowerCase()`.



S_{RESULT} = {ab,aB,Ab,AB} ∩ {aB,bA,ba} = {aB}
Symbolic String S
$S_{\text{POST-INVERSE}} \cap S_{\text{PRE-OPERATION}}$
$S_{\text{PRE-OPERATION}}$ = {aB,bA,ba}
$S_{\text{POST-INVERSE}}$ = {ab,aB,Ab,AB}
S.toLowerCase()
S.invToLowerCase()
$S_{\text{POST-OPERATION}}$ = {ab,ba}
$S_{\text{POST-PREDICATE}}$ = {ab}
S.endsWith(“b”)

Figure 3.6: Handling Over-Approximation

3.1.8 Maintaining Related Values

Unsound results are returned when an inverse string operation needs to maintain the relationship of outgoing strings. However, single-track automata models cannot maintain such relations. Each string model represents one string, with no intrinsic way to specify a relationship with a string from another node. Previous work examines methods of handling string relations using complex, multi-track automata that are memory and computationally expensive [18, 19]. The approach taken here focuses on completeness, and it propagates singleton values as matched pairs for related concrete strings. To ensure soundness, the framework produces all matched pairs through iteration.

The related value node `evaluate(`*inputNode*`,` *sourceIndex*`)` function is presented in Algorithm 6. The function maintains the list of related values returned by the inverse string operation, and either returns values from this list if available, or uses the inverse string operation to generate more values from remaining input. The input is retrieved from the calling node on line 2. The alogrithm selects concrete values from these inputs, and the while loop initiated on line 3 continues until all inputs are exhuasted or solutions are found. Line 4-5 remove a concrete value from the inputs. Lines 6-7 retrieve string models from the target and argument nodes. Line 8 calls the inverse operation that returns a set of tuples, each tuple containing a matched pair of concrete values that satisfy both the target and argument nodes. The while loop initiated on line 9 continues until all of these tuples have been propagated or a solution is found. Line 10 removes a single tuple from the set. It is split into two singleton string models on lines 11-12. The singleton string models are intersected with the forward results on lines 13-14. The singleton string models are placed in the output set on lines 15-16. The `evaluate(`$inputNode$`, `$sourceIndex$`)` function for both the target and argument nodes is called on line 17. If both of these calls return true, then the algorithm returns true. If no solution is found and all available values have been explored, the algorithm returns false.

Algorithm 6 Evaluate Function for Related Value Operations

```
    ▷ Each node has a pointer to targetNode
    ▷ Each node exposes an outputMap
    ▷ Each node has an internal solutionSet
    ▷ Each node has reference to argumentNode
 1: function EVALUATE(inputNode, sourceIndex)
 2:     inputs ← inputNode.outputSet(sourceIndex)
 3:     while not inputs.isEmpty() do
 4:         input ← inputs.getShortest()
 5:         inputs ← inputs.minus(input)
 6:         targetModel ← targetNode.getModel()
 7:         argumentModel ← argumentNode.getModel()
 8:         Set of Tuples outputs ← inverseOperation(targetModel,argumentModel)
 9:         while not outputs.isEmpty() do
10:             Tuple split ← outputs.remove()
11:             postOpTarget ← split.get1()
12:             postOpArgument ← split.get2()
13:             postOpTarget ← intersect(postOpTarget, targetNode.forwardResult)
14:             postOpArgument ← intersect(postOpArgument,
    argumentNode.forwardResult)
15:             outputMap.put(1,postOpTarget)
16:             outputMap.put(2,postOpArgument)
17:             if argumentNode.evaluate(thisNode,2) ∧
    targetNode.evaluate(thisNode,1) then
18:                 return true
19:             end if
20:         end while
21:     end while
22:     return false ▷ fallback to find new solutions
23: end function
```

Figure 3.7 presents the flow of related symbolic strings through a concatenation operation, where input strings S_1, S_2 are defined with parameters Σ={a,b},

$1 \le k \le 2$. The post-predicate values for S_3 are displayed below the `invConcat()` node. In this example, the string value `"aaa"` (underlined in the figure) is selected as input to the `invConcat()` operation. The `invConcat()` operation returns a list of valid prefix / suffix pairs for further computations. In this case it returns tuples `(a, aa)` and `(aa, a)`. The first singleton values propagated are $S_1 =$ `"a"`, $S_2 =$ `"aa"`. If a fallback occurs or multiple solutions are needed, then the next evaluation returns $S_1 =$ `"aa"`, $S_2 =$ `"a"`. After that, another singleton is removed from the set of incoming values and the process continues. If no further pairs are available and there are no further incoming values available, a fallback sequence is initiated. It is important to note that the `invConcat()` exhaustively returns all of the prefix / suffix pairs, which makes this operation sound and complete.

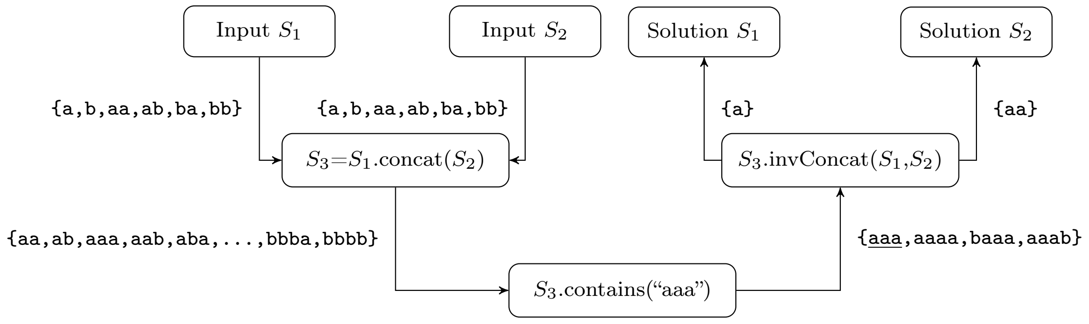


Figure 3.7: Handling Related Inputs

This approach addresses the goals of prioritizing a complete solution over a sound solution in a single iteration, while maintaining relationships between string inputs. Note that the term *unsound result* when applied to an inverse string operation using this approach means it has not *yet* returned all of the values in a sound result, but does not indicate that it cannot produce a sound result if it is allowed to exhaust the incoming values.

3.1.9 Termination

The algorithm terminates since the TCG is acyclic, and each node has a finite number of values that it can propagate backwards. It finds a solution because it propagates all feasible predicate strings backwards to each input, and one of those strings must lead to a solution.

3.1.10 Complexity

The nodes of the TCG can be partitioned into two groups: source and sink nodes, and inverse operation (inner) nodes. Source and sink nodes are predicates, inputs, and constants. These three node types simply propagate values, with the input nodes taking the additional step of checking the solution set for consistency. Here we define an input size as the number of values the symbolic string inputs represent. Since the input size does not affect these nodes, they compute in constant time. Note that the number of values a symbolic string input represents is determined by the alphabet and the length of input strings.

Inverse operation nodes can further be categorized into two types: Those that return a full solution (sound) and those that do not (unsound). The complexity of inverse operations of sound nodes depend on the input size and has growth linear with the automata size. The complexity of inverse operations for the nodes that compute unsound results has non-linear growth with the input size. A worst-case scenario, therefore, is a constraint containing multiple unsound operations over related variables such as $\texttt{s1.concat(s1)}^{-1}$.

Consider unsound nodes in the TCG. We define d as the size of their inputs, set in this case the number of string values output by the previous node. Note that d depends on the length and alphabet size of the symbolic string inputs (see Section 5.3 for more details). We define p as the maximum number of matching tuples of values for each d input value that such node can produce. In a worst case scenario all of these pairs need to be propagated to the descendants of the node. We define m as the number of inverse operations in the TCG. Then the resulting recurrence relationship is $f(m) = d \times p \times f(m-1)$. This reduces to $f(m) = d^m \times p^m$, which is the worst case number of traversals of the TCG.

3.1.11 Limitations

The algorithm is limited in the handling of multiple predicates. Although a constraint graph may have multiple predicates present, the algorithm processes one predicate at a time, without consideration for the presence of others. In practical terms, the algorithm cannot reliably process related predicates such as embedded "If" statements. It will solve each independently and cannot backtrack to previously solved predicates. Extension of the algorithm to multiple related predicates is left for future work.

3.2 Inverse String Operations

Nodes in the TCG ally with inverse string operations for the backward analysis. The following list itemizes the properties of an inverse string operation:

- All operations must return complete results.
- Some operations return sound and complete results on the first evaluation.
- When relationships between strings must be maintained, an operation returns an unsound result containing a set of singleton pairs.

- Operations that return unsound results can be repeatedly queried until all possible results are returned.
- When over-approximation occurs, inverse results are intersected with pre-string operation values to obtain a complete result.

3.2.1 Formal Definitions and Algorithms

The formal definitions are based on the following assumptions. First, each inverse operation takes as input an acyclic-automata $\mathcal{A}$ encoding all of the possible strings from the previous inverse operation. However, the inverse concatenation operation only considers singletons to compute the prefix and suffix inverses. Second, all of the string operations modeled in the forward analysis such as delete and insert are available, as well as standard automata operations such as union and intersection. Third, all integers used in arguments of string operations such as substring have concrete values.

Inverse String Operation `t.concat(String arg)`$^{-1}$:

From the input automata, a single string s is removed and encoded in $\mathcal{A}$. Then the inverse is defined as:

$\{(t, arg) \mid \forall i \in [0, |s|]\ t = \mathcal{A}.\text{substring}(0, i) \wedge arg = \mathcal{A}.\text{substring}(i)\}$

The inverse of `concat` operates on a single string s and splits it into all possible prefix and suffix combinations. This inverse produces a set of (t, arg) tuples for each possible i split. The pseudocode for inverse concatenate is presented in Algorithm 7. At line 3 it iterates over the length of the prefix. Each iteration builds a prefix / suffix tuple on lines 4-5. A new tuple is created and added to the result set on line 6. A set of tuples containing all feasible prefix / suffix pairs is returned on line 8. The `evaluate(`$inputNode$`,` $sourceIndex$`)` removes infeasible tuples from the result tuples.

Algorithm 7 Algorithm for INVCONCAT()

```
1: function INVCONCAT(prefixModel, suffixModel)
2:     resultTuples = {}
3:     for length ← 0 to prefixModel.BOUND() do
4:         newPrefix ← thisModel.SUBSTRING(0, length)
5:         newSuffix ← thisModel.SUBSTRING(length)
6:         resultTuples.ADD(new Tuple(newPrefix, newSuffix))
7:     end for
8:     return resultTuples
9: end function
```

Inverse String Operation `t.delete(int start, int end)`$^{-1}$:

Let $\mathcal{A}_{\text{substr}}$ have $L(\mathcal{A}_{\text{substr}}) = \Sigma^{end-start}$, that is all strings of length `(end - start)`. The inverse is defined as:

$\mathcal{A}.\text{insert}(\mathcal{A}_{\text{substr}}, start)$

All possible strings of length $(end - start)$ are inserted into $\mathcal{A}$. The pseudocode for inverse delete is presented in Algorithm 8. A new symbolic string accepting all strings of the length of the deleted portion is created on line 2. The new symbolic string is inserted into the target automaton on line 3. Subsequent intersection with forward results occurs in the calling `evaluate(`*inputNode*`,` *sourceIndex*`)` function.

Algorithm 8 Algorithm for INVDELETE()

```
1: function INVDELETE(start, end)
2:     insertModel ← createModel($\Sigma^{end-start}$)
3:     resultModel ← thisModel.insert(start, insertModel)
4:     return resultModel
5: end function
```

Inverse String Operation `t.deleteCharAt(int index)`$^{-1}$:

The inverse is defined in terms of the `t.delete(int start, int end)`$^{-1}$.

The inverse is:

`t.delete(int index, int index + 1)`$^{-1}$

The pseudocode for inverse deleteCharAt is presented in Algorithm 9. Line 2 assigns the value of a call to the invDelete function with arguments that evaluate to a string of length one.

Algorithm 9 Algorithm for invDeleteCharAt()

```
1: function invDeleteCharAt($index$)
2:     $resultModel \leftarrow thisModel$.invDelete($index, index + 1$)
3:     return $resultModel$
4: end function
```

Inverse String Operation `t.insert(int index, String arg)`$^{-1}$:

Let $\mathcal{A}$ be the target string model. Let m be $|arg|$, where arg is a concrete string, then the inverse is defined as:

$\mathcal{A}$.delete(index, m)

This inverse operation deletes a substring of length m at the specified location. The algorithm for inverse insert is presented in Algorithm 10. Line 2 assigns the value returned by a delete invocation, which removes the inserted portion from the target symbolic string.

Algorithm 10 Algorithm for invInsert()

```
1: function invInsert($index$, $arg$)
2:     $resultModel \leftarrow thisModel$.delete($index$, $index + |arg|$)
3:     return $resultModel$
4: end function
```

Inverse String Operation `t.replace(char oldChar, char newChar)`$^{-1}$:

Let $\mathcal{A} = (Q, \Sigma, E, q_0, F)$ be the incoming automaton. Given the values of *oldChar* and *newChar*, define a new set of transitions $E_t = E \cup \{(p, \mathit{oldChar}, q) \mid (p, \mathit{newChar}, q) \in E\}$. The inverse creates a new automaton with a new set of transitions E_t, that is the automaton for the target becomes:

(Q, Σ, E_t, q_0, F)

This inverse operation adds additional transitions with *oldChar* labels to $\mathcal{A}$ between states that already have *newChar* as labels. The pseudocode for inverse replace is presented in Algorithm 11. Line 2 extracts the underlying automaton from the symbolic string, since the function directly modifies it. The sets of transitions are initialized on line 3. Lines 4-8 iterate over all of the incoming automata transitions, adding a new *oldChar* transition to the new transition set for every *newChar* transition. Line 9 creates a new automaton and string model. Subsequent intersection with forward results occurs in the calling `evaluate(`$inputNode$`, `$sourceIndex$`)` function.

Algorithm 11 Algorithm for INVREPLACE()

```
1: function INVREPLACE(oldChar, newChar)
2:     newAutomaton ← thisModel.GETAUTOMATON()
3:     E ← newAutomaton.getTransitions()
4:     for all TRANSITION e ∈ E do
5:         if e.char == newChar then
6:             E.addTransition(e.target, oldChar, e.dest)
7:         end if
8:     end for
9:     resultModel ← new StringModel(newAutomaton)
10:    return resultModel
11: end function
```

Inverse String Operation `t.reverse()`$^{-1}$:

Let $\mathcal{A}$ be the target string model. The inverse is defined as:

$\mathcal{A}.reverse()$

The reverse operation is the inverse of itself and has no over-approximation. The pseudocode for inverse reverse is presented in Algorithm 12. The algorithm simply invokes reverse on the string model on line 2.

Algorithm 12 Algorithm for INVREVERSE()

```
1: function INVREVERSE( )
2:     resultModel $\leftarrow$ thisModel.reverse()
3:     return resultModel
4: end function
```

Inverse String Operation `t.toLowerCase()`$^{-1}$:

Let $\mathcal{A} = (Q, \Sigma, E, q_0, F)$ be the incoming target automaton. We define a new set of transitions $E_t = E \cup \{(p, upperCase(char), q) \mid (p, char, q) \in E\}$. The inverse operation creates a new automaton with the new set of transitions E_t. The inverse is defined as the new automaton:

(Q, Σ, E_t, q_0, F)

The inverse adds a transition with an upper case character between states that have transitions on a corresponding lower case character. The algorithm for inverse toLowerCase is presented in Algorithm 13. A reference to the underlying automaton is created on line 2. Lines 4-6 iterate over the transitions and characters. Line 5 adds an upper case transition for every character. Subsequent intersection with forward results occurs in the calling `evaluate(`*inputNode*`,` *sourceIndex*`)` function.

Algorithm 13 Algorithm for INVTOLOWERCASE()

```
1: function INVTOLOWERCASE( )
2:     newAutomaton ← thisModel.GETAUTOMATON()
3:     E ← newAutomaton.getTransitions()
4:     for all TRANSITION $e \in E$ do
5:         E.addTransition(e.target, e.char.toUpper(), e.dest)
6:     end for
7:     resultModel ← new StringModel(newAutomaton)
8:     return resultModel
9: end function
```

Inverse String Operation `t.toUpperCase()`$^{-1}$:

Let $\mathcal{A} = (Q, \Sigma, E, q_0, F)$ be the incoming target automaton. We define a new set of transitions $E_t = E \cup \{(p, lowerCase(char), q) \mid (p, char, q) \in E\}$. The inverse operation creates a new automaton with the new set of transitions E_t. The inverse is defined as the new automaton:

(Q, Σ, E_t, q_0, F)

The inverse adds a transition with a lower case character between states that have transitions on a corresponding upper case character. The algorithm for inverse toUpperCase is presented in Algorithm 14. A reference to the underlying automaton is created on line 2. Lines 4-6 iterate over the transitions and characters. Line 5 adds a lower case transition for every character. Subsequent intersection with forward results occurs in the calling `evaluate(`*inputNode*`,` *sourceIndex*`)` function.

Algorithm 14 Algorithm for INVTOUPPERCASE()

```
1: function INVTOUPPERCASE( )
2:     newAutomaton ← thisModel.GETAUTOMATON()
3:     E ← newAutomaton.getTransitions()
4:     for all TRANSITION e ∈ E do
5:         E.addTransition(e.target, e.char.toLower(), e.dest)
6:     end for
7:     resultModel ← new StringModel(newAutomaton)
8:     return resultModel
9: end function
```

Inverse String Operation `t.substring(int start, int end)`$^{-1}$:

Let $\mathcal{A}$ be the incoming target automata. Define m as the maximum length of string in the forward results $\mathcal{A}_0^F$ and an automaton $\mathcal{A}_{\text{prefix}}$ such that $L(\mathcal{A}_{\text{prefix}}) = \Sigma^{start}$. Define automaton $\mathcal{A}_{\text{suffix}}$ such that $L(\mathcal{A}_{\text{suffix}}) = \Sigma^{m-end}$. Then the inverse is defined as follows:

$\mathcal{A}_{\text{prefix}}.concat(\mathcal{A}).concat(\mathcal{A}_{\text{suffix}})$

The pseudocode for inverse substring(start, end) is presented in Algorithm 15. It creates a prefix of known length *start* and a suffix of length $m - end$ accepting all strings to the given length. It then concatenates the $\mathcal{A}_{\text{prefix}}$, $\mathcal{A}$, and $\mathcal{A}_{\text{suffix}}$. Line 2 creates a string model that accepts strings up to the length of the removed prefix. Line 3 creates a suffix model that is at least as long as the removed suffix. Line 4 concatenates the prefix, target and suffix together. Subsequent intersection with forward results occurs in the calling `evaluate(`$inputNode$`, `$sourceIndex$`)` function.

Algorithm 15 Algorithm for INVSUBSTRING(START, END)

```
1: function invSubstring(start, end)
2:     prefixModel ← createModel($\Sigma^{start}$)
3:     suffixModel ← createModel($\Sigma^{m-end}$)
4:     resultModel ← prefixModel.concat(thisModel).concat(suffixModel)
5:     return resultModel
6: end function
```

Inverse String Operation `t.substring(int start)`$^{-1}$:

Let $\mathcal{A}$ be the incoming target automata. Define automata $\mathcal{A}_{\text{prefix}}$ such that $L(\mathcal{A}_{\text{prefix}}) = \Sigma^{start}$. The inverse is defined as:

$\mathcal{A}_{\text{prefix}}.concat(\mathcal{A})$

The pseudocode for inverse substring(start) is presented in Algorithm 16. It creates a prefix of known length *start* accepting all strings to the given length. It then concatenates the $\mathcal{A}_{\text{prefix}}$ and $\mathcal{A}$. A prefix model is created that accepts all strings up to the length of the removed prefix on line 2. Line 3 concatenates the prefix and target. Subsequent intersection with forward results occurs in the calling `evaluate`$(inputNode,\ sourceIndex)$ function.

Algorithm 16 Algorithm for INVSUBSTRING(START)

```
1: function INVSUBSTRING($start$)
2:     $prefixModel \leftarrow$ createModel($\Sigma^{start}$)
3:     $resultModel \leftarrow prefixModel$.concat($thisModel$)
4:     return $resultModel$
5: end function
```

Inverse String Operation `t.trim()`$^{-1}$:

Let $\mathcal{A}$ be the incoming target automata. Define w as the whitespace character, and m as the maximum length of string in the forward results $\mathcal{A}_0^F$. Define $\mathcal{A}_{\text{padding}}$ such that $L(\mathcal{A}_{\text{padding}}) = w^m$. Then the inverse is defined as:

$\mathcal{A}_{\text{padding}}.\text{concat}(\mathcal{A}.\text{concat}(\mathcal{A}_{\text{padding}}))$

The pseudocode for inverse trim is presented in Algorithm 17. The inverse operation pads the strings encoded in $\mathcal{A}$ with the whitespace character such that all strings are at least as long as the longest string in $\mathcal{A}_0^F$. A string model as long as the maximum string length is created on line 3 that accepts all strings comprised of the whitespace character. The prefix, target and suffix are concatenated on line 4. Subsequent intersection with forward results occurs in the calling `evaluate(`*inputNode*`,` *sourceIndex*`)` function.

Algorithm 17 Algorithm for INVTRIM()

```
1: function INVTRIM( )
2:     alphabet $\Sigma \leftarrow w$
3:     paddingModel $\leftarrow$ createModel($\Sigma^m$)
4:     resultModel $\leftarrow$ paddingModel.concat(thisModel.concat(paddingModel))
5:     return resultModel
6: end function
```

SECTION 4

IMPLEMENTATION

The solver is part of a larger input generation framework shown in Figure 4.1. The solver has been completed, extending the code from previous research comparing the performance of string solvers [10][1] and the suitability of automata for modeling symbolic strings [16][2]. These in turn are largely based on Java String Analyzer (JSA) and the dk.brics automaton library [4][3]. The input generation framework is part of the public repository at
`https://github.com/BoiseState/string-constraint-counting`.

The framework consists of the following components, illustrated in Figure 4.1:

Input Generator - This is the main entry point for the system. It instantiates the reporter, parser, and solver. It instantiates the reporter `run()` function, which in turn uses the parser and solver to generate inputs through backward analysis.

Parser - Parses input graphs encoding into internal data structure.

Solver - Contains forward and backward analysis logic as well as the symbolic string table.

[1]`https://github.com/BoiseState/string-constraint-solvers`
[2]`https://github.com/BoiseState/string-constraint-counting`
[3]`http://www.brics.dk/JSA/, https://www.brics.dk/automaton/`

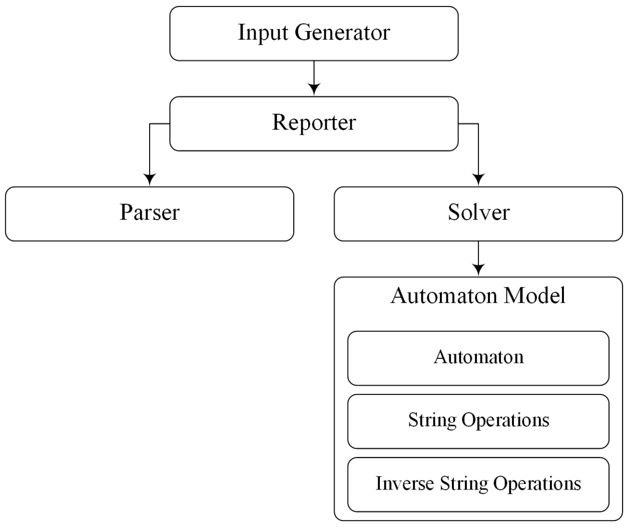


Figure 4.1: Input Generator Components

Reporter - Bridges the parser and solver components, and provides output from the system.

Automata Model - Contains the acyclic automata and implementations of string operations and their inverse.

Table 4.1 presents Software metrics of the initial (string-constraint-counting) and current (inverse-testing) codebases. The implementation adheres to object oriented design principles, with proper type hierarchy represented by interfaces, abstract classes, and concrete classes. This results in a larger increase in the number of classes and interfaces in comparison to lines of code.

Table 4.1: Metrics for Initial and Current Codebase

Code Base	**Files**	**Classes**	**Interfaces**	**Lines**
string-constraint-counting	74	66	8	∼28,000
inverse-string-testing	150	130	19	∼31,000

Table 4.2 contains the external dependencies required to build the input gen-

eration system.

Table 4.2: Major Dependencies

Library	**Source**	**Version**
Apache Commons Math	Apache Software Foundation	3.6
jackson-core	FasterXML, LLC.	2.7.2
jackson-databind	FasterXML, LLC.	2.7.2
jackson-annotations	FasterXML, LLC.	2.7.2
jgraph	Barak Naveh et. al.	5.13
jgraphx	Barak Naveh et. al.	2.0.0.1
jgrapht-core	Barak Naveh et. al.	0.9.1
jgrapht-ext	Barak Naveh et. al.	0.9.1
dk.brics.automaton	Anders Moller	1.11-8
dk.brics.string	Anders Moller et. al.	2.1-1
hamcrest	hamcrest.org	1.3

4.1 Inverse String Operation Classes

Interfaces and base abstract classes specify the inverse string operations and methods necessary to perform the backward analysis. The acyclic-automata model is extended with the inverse string operations shown in Table 4.3. String operations may have multiple inverse string operations, depending on the argument types passed to the string operation, i.e., whether the argument is concrete or symbolic. The *Sound* column indicates whether the inverse operation returns a sound result on the first evaluation. The *Over* column indicates whether the inverse operation over-approximates.

Table 4.3: String and Inverse String Operations

String Operation	**Inverse Operation(s)**	**Sound**	**Over**
concat(arg)	invConcat(Con)	Yes	No
	invConcat(Sym)	No	Yes
delete(int start, int end)	invDelete(int, int)	Yes	Yes
insert(int offset, arg)	invInsert(int, Con)	Yes	Yes
	invInsert(int, Char)	Yes	No
replace(arg find, arg repl)	invReplace(Char, Char)	Yes	Yes
	invReplace(Con, Con)	Yes	Yes
reverse()	invReverse()	Yes	No
substring(int start, int end)	invSubstring(int, int)	Yes	Yes
substring(int start)	invSubstring(int)	Yes	Yes
toLowercase()	invToLowerCase()	Yes	Yes
toUppercase()	invToUpperCase()	Yes	Yes
trim()	invTrim()	Yes	Yes

4.2 Solver

Interfaces and base abstract classes include the methods for supporting backward analysis and performing inverse string operations. The solver class has been extended to support the inverse string operations implemented in the acyclic-automata string model.

The solver takes as input a constraint graph stored in a JSON format. The JSON file encodes the edge and vertices information along with the alphabet definition. Input length can be optionally encoded in the file or specified through command line arguments.

Benchmark constraint graphs are collected in previous work [10,16] by instrumenting real-world Java programs.

4.3 Integration with Symbolic Pathfinder

The input generation system is loosely integrated with Symbolic Pathfinder (SPF). Currently SPF does not support many of the non-injective functions that the solver can currently perform. For those benchmarks that include only those functions SPF supports, a semi-automated workflow has been developed. First, SPF analyzes the Java program and produces a path condition, which is parsed into a JSON file for input into the system. Figure 4.2 shows the workflow for this process. Figure 4.3 shows an excerpt from a Java program used for correctness testing and the resulting path condition from SPF. Figure 4.4 shows the resulting constraint graph.

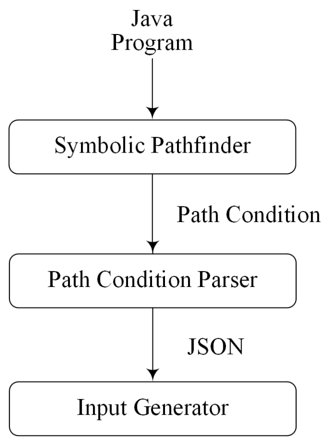


Figure 4.2: Symbolic Pathfinder Data Flow

```
public class BSU_SCS_Inverse_case_6 {
...
  // method under test
  public static void mut(String r5) {
    if (r5.substring(4, 7).equals("two")) {
      pathTaken = path != 0 ? 1 : 0;
      return;
    } else {
      pathTaken = path != 0 ? 2 : 0;
      return;
    }
  }
}

```

(a) Method with string input

```
(r5-1-SYMSTRING.substr(4,7) equals CONST-two)
```

(b) Path Conditions from SPF

Figure 4.3: Example SPF Input and Output

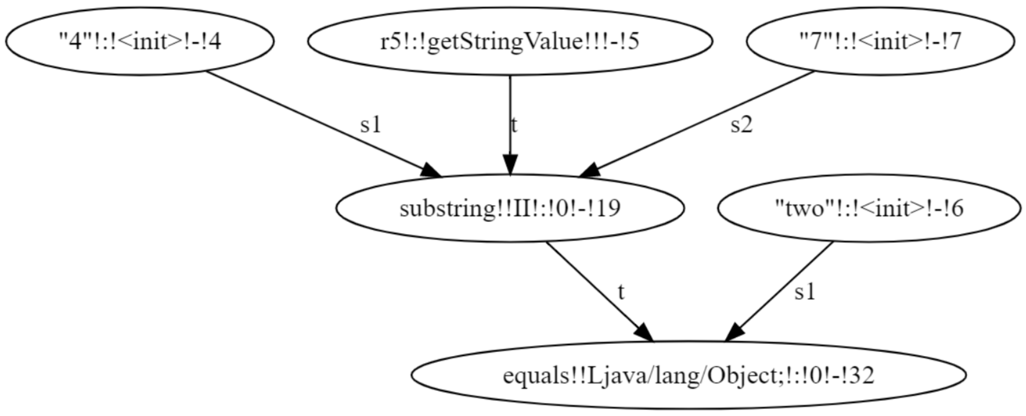


Figure 4.4: Test Case Constraint Graph

SECTION 5

EVALUATION

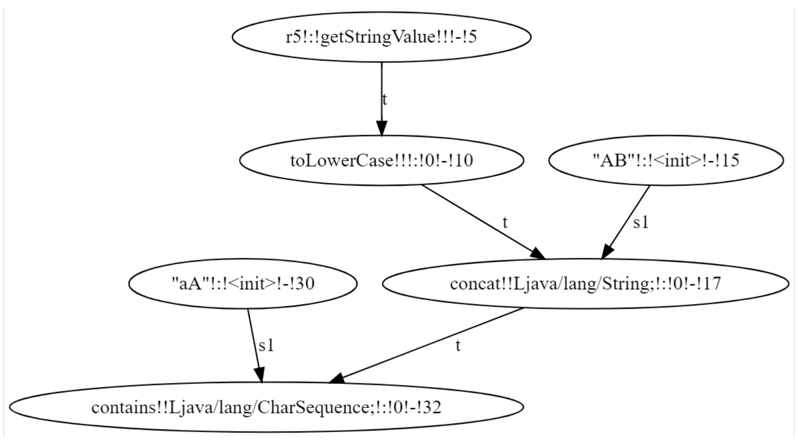
This section provides details on the correctness verification as well as the answer to research question **RQ3**: *Is the solution practical and effective?*

5.1 Correctness

Fifteen synthetic test cases are used to verify correctness, developed specifically for this solver. They are implemented as Java programs where string inputs determine execution paths, taking as input concrete string values and expected execution paths for them. Figure 5.7 presents the test flow diagram from a Java program through verification results. The Java test case program is used as the input into SPF, with `methodUnderTest()` specified as the target method for analysis. SPF generates a path condition which is then parsed into a JSON file containing the constraint graph. This in turn is used as input into the Input Generation framework which uses the solver to generate a solution for each parameter of `methodUnderTest()`. Correctness is verified by executing the Java test case program with the solution values and observing the results. The test cases are designed such that they indicate success or failure based on the expected and actual path taken with the computed input values. Some of these test programs incorporate non-injective and unsound operations. Thus, Figure 5.1 presents a test case incorporating non-injective and unsound operations on line 26. This code corresponds to the constraint graph in Figure 5.2. Other test cases take multiple inputs (Figures 5.5 and 5.6) and have multiple outgoing edges from a node (Figures 5.3 and 5.4) in their constraint graphs. These test cases compose the correctness benchmark.

```
 1  public class BSU_SCS_Inverse_case_1 {
 2    static int path = 0;
 3    static int pathTaken = 0;
 4    static String r5;
 5    static boolean test = false;
 6
 7    public static void main(String[] args) {
 8      if (args.length == 2) {
 9        path = Integer.parseInt(args[0]);
10        r5 = args[1];
11        test = true;
12        System.out.println("\nTEST: Args ... " + r5 + "\nTEST: Path ... " + path);
13      } else {
14        r5 = "A"; }
15
16      methodUnderTest(r5);
17
18      if (test) {
19        if (path - pathTaken == 0) {
20          System.out.println("TEST: SUCCESS");
21        } else {
22          System.out.println("TEST: FAILURE");
23        } } }
24
25    public static void methodUnderTest(String r5) {
26      if (r5.toLowerCase().concat("AB").contains("aA")) {
27        pathTaken = path != 0 ? 1 : 0;
28        return;
29      } else {
30        pathTaken = path != 0 ? 2 : 0;
31        return;
32      } } }
33
```

Figure 5.1: Non-Injective and Unsound Operations Test Case Code



r5!:!getStringValue!!!-!5
t
toLowerCase!!!:!0!-!10
"AB"!:!<init>!-!15
t
s1
"aA"!:!<init>!-!30
concat!!Ljava/lang/String;!:!0!-!17
s1
t
contains!!Ljava/lang/CharSequence;!:!0!-!32

Figure 5.2: Non-Injective and Unsound Operations Constraint Graph

```
public class BSU_SCS_Inverse_case_1a {
  static int path = 0;
  static int pathTaken = 0;
  static String r5;
  static boolean test = false;

  public static void main(String[] args) {
    if (args.length == 2) {
      path = Integer.parseInt(args[0]);
      r5 = args[1];
      test = true;
      System.out.println("\nTEST: Args ... " + r5 + "\nTEST: Path ... " + path);
    } else {
      r5 = "A"; }

    methodUnderTest(r5);

    if (test) {
      if (path - pathTaken == 0) {
        System.out.println("TEST: SUCCESS");
      } else {
        System.out.println("TEST: FAILURE");
      } } }

  public static void methodUnderTest(String r5) {
    if (r5.contains("aA")) {
      if (r5.contains("AA")) {
        pathTaken = path != 0 ? 1 : 0;
      }
      return;
    } else {
      pathTaken = path != 0 ? 2 : 0;
      return;
    } } }

```

Figure 5.3: Multiple Outgoing Edges Test Case Code

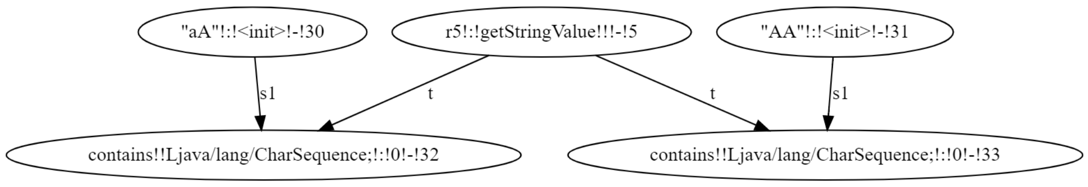

"aA"!:!<init>!-!30
r5!:!getStringValue!!!-!5
"AA"!:!<init>!-!31
s1
t
t
s1
contains!!Ljava/lang/CharSequence;!:!0!-!32
contains!!Ljava/lang/CharSequence;!:!0!-!33

Figure 5.4: Multiple Outgoing Edges Constraint Graph

```java
public class BSU_SCS_Inverse_case_2b {
  static int path = 0;
  static int pathTaken = 0;
  static String r5,r6;
  static boolean test = false;

  public static void main(String[] args) {
    if (args.length == 3) {
      path = Integer.parseInt(args[0]);
      r5 = args[1];
      r6 = args[2];
      test = true;
      System.out.println("\nTEST:Args...r5: "+r5+" r6: "+r6+"\nTEST: Path..."+path);
    } else {
      r5 = "one";
      r6 = "two"; }

    methodUnderTest(r5, r6);

    if (test) {
      if (path - pathTaken == 0) {
        System.out.println("TEST: SUCCESS");
      } else {
        System.out.println("TEST: FAILURE");
      } } }

  public static void methodUnderTest(String r5, String r6) {
    if (r5.concat(r6).contains("onetwo")) {
      pathTaken = path != 0 ? 1 : 0;
      return;
    } else {
      pathTaken = path != 0 ? 2 : 0;
      return;
    } } }

```

Figure 5.5: Multiple Inputs Test Case Code

The constraint graph file contains the size and description of the alphabet, and the bound on lengths of symbolic string inputs in addition to the constraint graph. In order to achieve reasonable runtimes on the correctness benchmark, bounds and

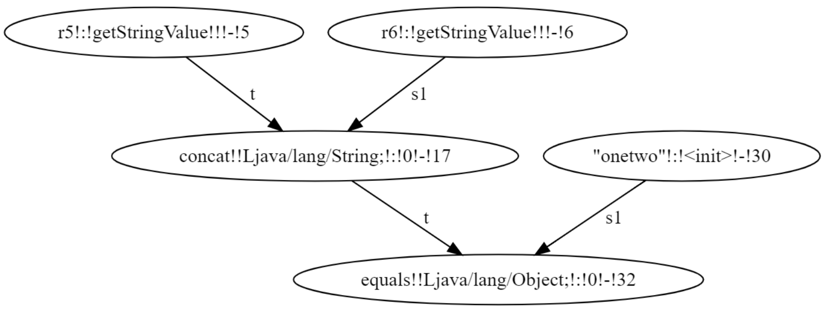

r5!:!getStringValue!!!-!5
r6!:!getStringValue!!!-!6
t
s1
concat!!Ljava/lang/String;!:!0!-!17
"onetwo"!:!<init>!-!30
t
s1
equals!!Ljava/lang/Object;!:!0!-!32

Figure 5.6: Multiple Inputs Constraint Graph

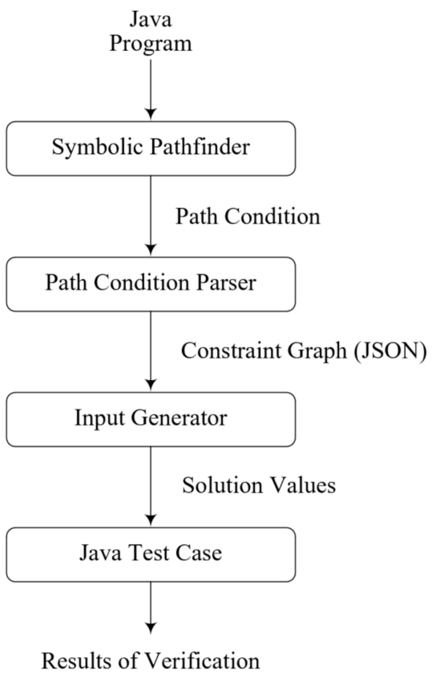
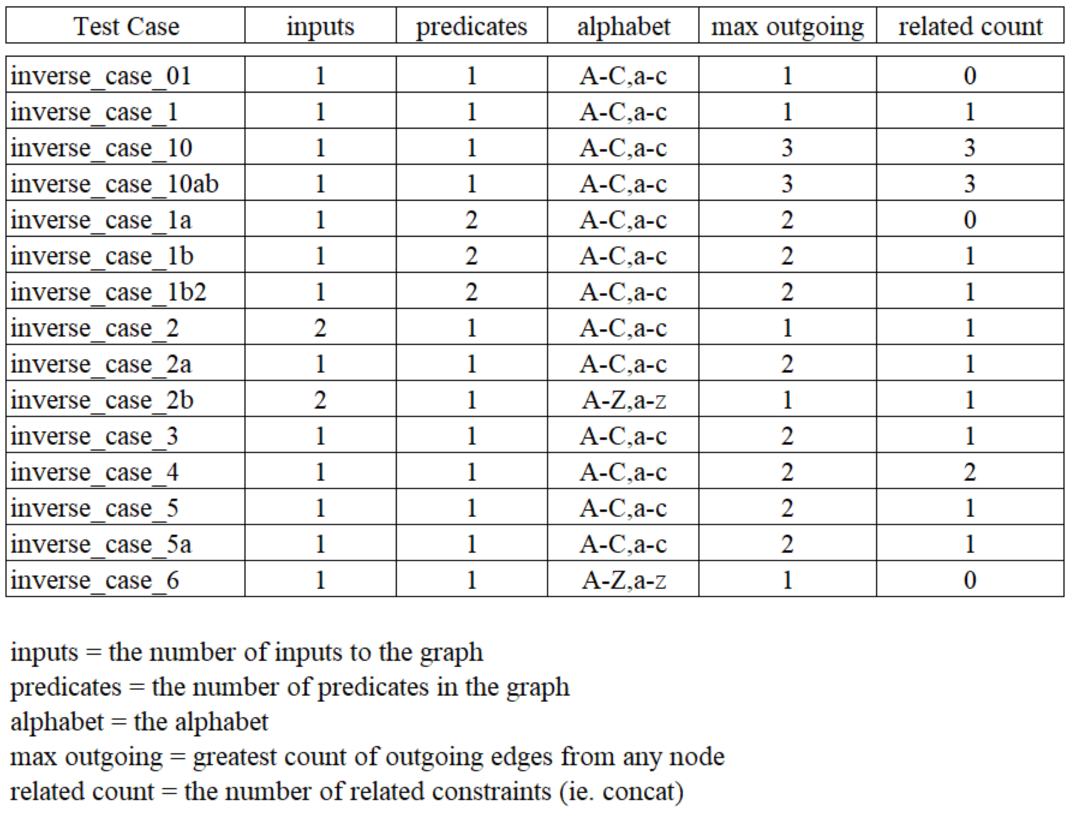


Figure 5.7: Test Flow

alphabets are set to small values such that testing completes quickly. Alphabets of (A-C, a-c) are used unless additional characters are needed (test cases 2b and 6). The testing iterates over length bounds due to unsoundness of the approach. At each iteration the length bound is incremented, starting with length $k = 1$ and doubling in length until $k = 16$.

Test case properties are presented in Table 5.1.

Table 5.1: Test Case Properties



Test Case	inputs	predicates	alphabet	max outgoing	related count
inverse_case_01	1	1	A-C,a-c	1	0
inverse_case_1	1	1	A-C,a-c	1	1
inverse_case_10	1	1	A-C,a-c	3	3
inverse_case_10ab	1	1	A-C,a-c	3	3
inverse_case_1a	1	2	A-C,a-c	2	0
inverse_case_1b	1	2	A-C,a-c	2	1
inverse_case_1b2	1	2	A-C,a-c	2	1
inverse_case_2	2	1	A-C,a-c	1	1
inverse_case_2a	1	1	A-C,a-c	2	1
inverse_case_2b	2	1	A-Z,a-z	1	1
inverse_case_3	1	1	A-C,a-c	2	1
inverse_case_4	1	1	A-C,a-c	2	2
inverse_case_5	1	1	A-C,a-c	2	1
inverse_case_5a	1	1	A-C,a-c	2	1
inverse_case_6	1	1	A-Z,a-z	1	0

inputs = the number of inputs to the graph
predicates = the number of predicates in the graph
alphabet = the alphabet
max outgoing = greatest count of outgoing edges from any node
related count = the number of related constraints (ie. concat)

5.1.1 Correctness Results

The correctness experiment is performed on an Intel(R) Xeon(R) CPU E5-2407 v2 @ 2.40GHz based system with 24GB of memory, running Fedora Linux version 33-1.2. The JVM used is OpenJDK version 11, with the target compatibility set to version 1.8. Each benchmark is executed three times with the average performance being reported. Table 5.2 presents performance timing and solution results of the correctness benchmark. The values reported in the input length columns is the time in milliseconds(ms) for the solver to compute a solution at the given length.

In those cases where the solver cannot find a solution (NS) it was verified manually that there were no possible solutions due to the given length being too restrictive. Timeouts of greater than 120 minutes are indicated with TO. Only the backward analysis time is presented in the table, however, the timeout calculation includes forward analysis time. The solutions column contains the computed solution to the input(s), and in cases where there is more than one solution only one chosen for an example. Note that once a solution is found at a given length, longer lengths continue to produce solutions unless a time out occurs, which serves as another measure of correctness of the implementation.

Table 5.2: Correctness Results

Test Case	Input Length					Solution
	1	2	4	8	16	
inverse_case_01	NS	14	20	55	42938	{A,a}
inverse_case_1	36	40	50	52	71	{A,a}
inverse_case_10	NS	3823	TO	TO	TO	{aa}
inverse_case_10ab	NS	48556	TO	TO	TO	{ab}
inverse_case_1a	NS	NS	10	41	102996	{aAA}
inverse_case_1b	NS	29	227	322	143488	{AAaa}
inverse_case_1b2	NS	40	56	84	46603	{aa}
inverse_case_2	32	43	46	52	71	{A,a}
inverse_case_2a	NS	44	59	59	79	{AA,Aa,aA,aa}
inverse_case_2b	NS	NS	90	98	550	{one,two}
inverse_case_3	49	85	94	258	TO	{A}
inverse_case_4	49	84	94	273	TO	{a}
inverse_case_5	37	41	42	54	TO	{a}
inverse_case_5a	NS	42	59	76	TO	{aa}
inverse_case_6	NS	NS	NS	61	120	ex.{AAAATwo}

NS	= No solution found
TO	= Timed out (>120m)

Times in ms

This testing process brought to light multiple faults in the code, but no fundamental errors in either the solvers algorithms or the logic of the inverse operations.

All solutions generated for the test cases successfully reach the expected locations when used as inputs to the Java benchmark programs.

To note, all runtime measurements increase as the length bound increases. This is an expected behavior, but some real-world program benchmarks presented in the next section exhibit a different trend.

Test cases `10` and `10ab` demonstrate expected inefficiencies of the solver with certain constraints. In particular, these test cases have multiple `concat(String arg)`$^{-1}$ constraints with data dependencies. In general, the performance bottleneck exists when establishing consistency between data dependent nodes. In the case of concatenation, the solver propagates partial results of inverse operations to maintain the relationship between the prefix and suffix pair. This can lead to many iterations of prefix / suffix choices and their propagation until satisfiable pairs are found. As length increases, more prefix / suffix pairs are available for iterations, causing an increase in runtime. Both test cases are only able to produce solutions at $k = 2$ before timing out. Figures 5.8 and 5.9 present the test code and constraint graph for test case `10ab`.

Reproducing Correctness Results

In order to aid in the reproduction of these results, a Docker file is available at `https://github.com/marlinroberts21/string-input-docker`. Utilizing this file, a user can build an image of a linux system housing the test input generation framework and correctness benchmarks.

```java
public class BSU_SCS_Inverse_case_10ab {
  static int path = 0;
  static int pathTaken = 0;
  static String r5;
  static boolean test = false;

  public static void main(String[] args) {
    if (args.length == 2) {
      path = Integer.parseInt(args[0]);
      r5 = args[1];
      test = true;
      System.out.println("\nTEST: Args ... " + r5 + "\nTEST: Path ... " + path);
    } else {
      r5 = "ab"; }

    methodUnderTest(r5);

    if (test) {
      if (path - pathTaken == 0) {
        System.out.println("TEST: SUCCESS");
      } else {
        System.out.println("TEST: FAILURE");
      } } }

  public static void methodUnderTest(String r5) {
    String s1 = r5.toUpperCase();
    if (r5.concat(s1).concat(s1.concat(r5)).contains("ab")) {
      pathTaken = path != 0 ? 1 : 0;
      return;
    } else {
      pathTaken = path != 0 ? 2 : 0;
      return;
    } } }

```

Figure 5.8: Related Unsound Operations Test Code

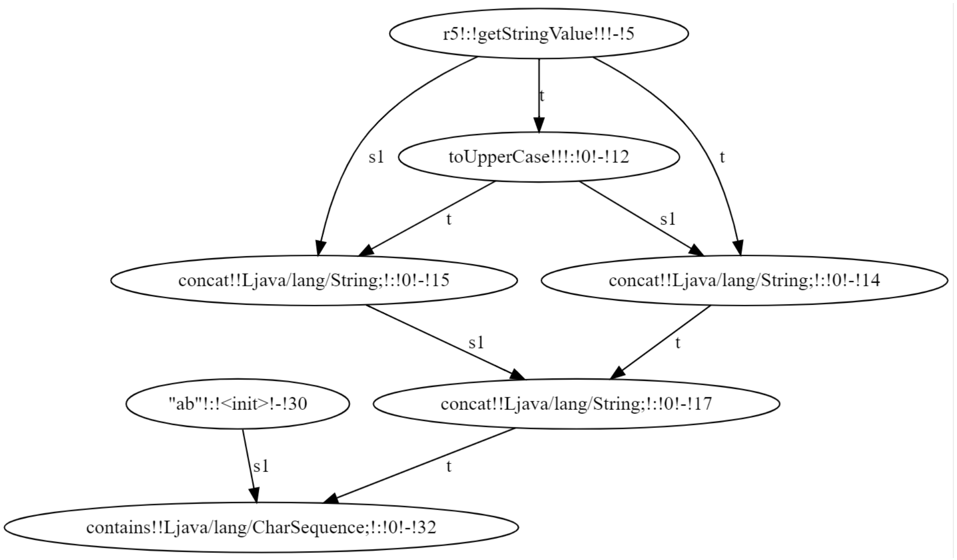

r5!:!getStringValue!!!-!5
t
s1
t
toUpperCase!!!:!0!-!12
t
s1
concat!!Ljava/lang/String;!:!0!-!15
concat!!Ljava/lang/String;!:!0!-!14
s1
t
"ab"!:!<init>!-!30
concat!!Ljava/lang/String;!:!0!-!17
s1
t
contains!!Ljava/lang/CharSequence;!:!0!-!32

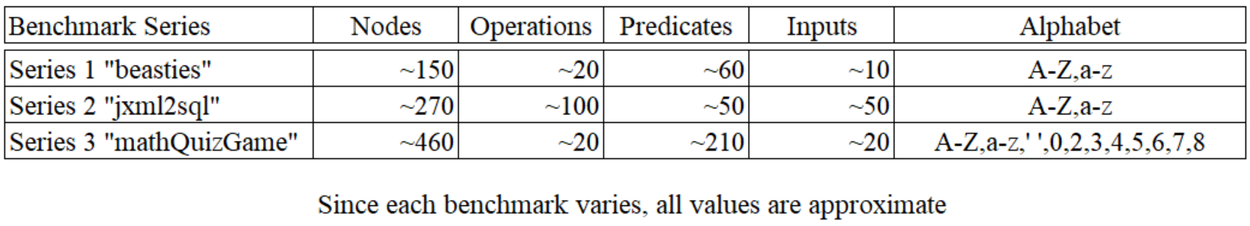
Figure 5.9: Related Unsound Operations Constraint Graph

5.2 Practicality

In order to answer the research question *Is the solution practical and effective?*, definitions of both practical and effective are needed. Practical means that the solver can be used in practice, in contexts of real-world scenarios, that include conditions and inputs. Effective means that the solver finds solutions for the inputs in those contexts.

To demonstrate practicality, it is necessary to have a set of inputs representing actual programs that incorporate common constructs and patterns found in Java programs. Previous work [10,16] obtained such a set of benchmarks from real-world Java programs and encoded them in constraint graphs, discussed previously. The benchmarks consist of a series of constraint graphs for three different Java programs, with each representing dynamic execution paths of programs with different concrete inputs. Table 5.3 presents the number of nodes, operations, predicates and inputs of each benchmark.

Table 5.3: Benchmark Properties



Benchmark Series	Nodes	Operations	Predicates	Inputs	Alphabet
Series 1 "beasties"	~150	~20	~60	~10	A-Z,a-z
Series 2 "jxml2sql"	~270	~100	~50	~50	A-Z,a-z
Series 3 "mathQuizGame"	~460	~20	~210	~20	A-Z,a-z,' ',0,2,3,4,5,6,7,8

Since each benchmark varies, all values are approximate

The solver is effective in that it finds solutions for all of the real-world benchmarks. Since the programs contain string operations which SPF does not support, it is not possible to incorporate them into the testing framework.

5.2.1 Results

Each benchmark series is executed in the same environment as the correctness benchmark. Similarly, each benchmark is executed three times and the average analysis time is reported.

Series One This series exhibited behavior unlike the correctness benchmarks in that approximately half of the benchmarks had a minimum runtime at length $k = 16$. Table 5.4 presents the runtimes as a ratio ($Runtime/MinimumRuntime$). The minimum runtime for each benchmark is shaded. Figure 5.10 presents a box plot of the ratio data from Table 5.4.

Series Two The series two execution times are presented in Table 5.5. This series does not have solutions at any length less than $k = 16$. This is due to the fact that the predicate arguments in this series can be length $k = 11$. For instance, *input*.`contains`(*"description"*) cannot have a solution for *input* at any $k \leq 11$. The two outliers identified in the box plot in Figure 5.11 have significantly fewer nodes than the other benchmarks in the same series. This led to significantly lower runtimes for both benchmarks.

Series Three Similar to series two, this series did not generate solutions until reaching a certain length, $k = 8$. At $k = 16$ all but two of the benchmarks reached the timeout of 120 minutes. The two outliers identified in the box plot in Figure 5.12 have significantly more nodes than the other benchmarks in the same series. This led to significantly higher runtimes for both benchmarks.

Table 5.4: Benchmark Timing Ratios - Series One

Benchmark	Input Length				
	1	2	4	8	16
beasties01	1.82	2.07	1.78	2.10	▨ 1.00
beasties02	1.00	1.12	1.02	1.15	▨ 1.00
beasties03	1.06	1.22	1.15	1.27	▨ 1.00
beasties04	1.11	1.24	1.04	1.09	▨ 1.00
beasties05	▨ 1.00	1.14	1.05	1.10	1.38
beasties06	▨ 1.00	1.10	1.05	1.15	1.49
beasties07	▨ 1.00	1.10	1.01	1.18	1.07
beasties08	▨ 1.00	1.05	1.03	1.09	1.38
beasties09	1.34	1.51	1.46	1.59	▨ 1.00
beasties10	▨ 1.00	1.07	1.05	1.12	2.39
beasties11	▨ 1.00	1.08	1.07	1.08	1.01
beasties12	1.05	1.01	▨ 1.00	1.10	1.74
beasties13	▨ 1.00	1.08	1.07	1.07	1.37
beasties14	1.41	1.43	1.52	1.58	▨ 1.00
beasties15	1.54	1.66	1.69	1.61	▨ 1.00
beasties16	▨ 1.00	1.08	1.03	1.16	1.96
beasties17	▨ 1.00	1.09	1.01	1.20	1.11
beasties18	1.10	1.19	1.12	1.24	▨ 1.00
beasties19	▨ 1.00	1.08	1.04	1.21	1.39
beasties20	1.12	1.23	1.16	1.27	▨ 1.00
beasties21	▨ 1.00	1.09	1.00	1.20	1.45
beasties22	1.01	1.10	1.04	1.22	▨ 1.00
beasties23	▨ 1.00	1.08	1.03	1.18	1.40
beasties24	1.42	1.51	1.48	1.55	▨ 1.00
beasties25	▨ 1.00	1.11	1.09	1.17	1.34
beasties26	▨ 1.00	1.07	1.01	1.08	1.53
beasties27	1.25	1.31	1.22	1.33	▨ 1.00
beasties28	▨ 1.00	1.08	1.02	1.17	1.49
beasties29	1.20	1.29	1.21	1.32	▨ 1.00
beasties30	▨ 1.00	1.05	1.00	1.15	1.23

▨ = Lowest Runtime

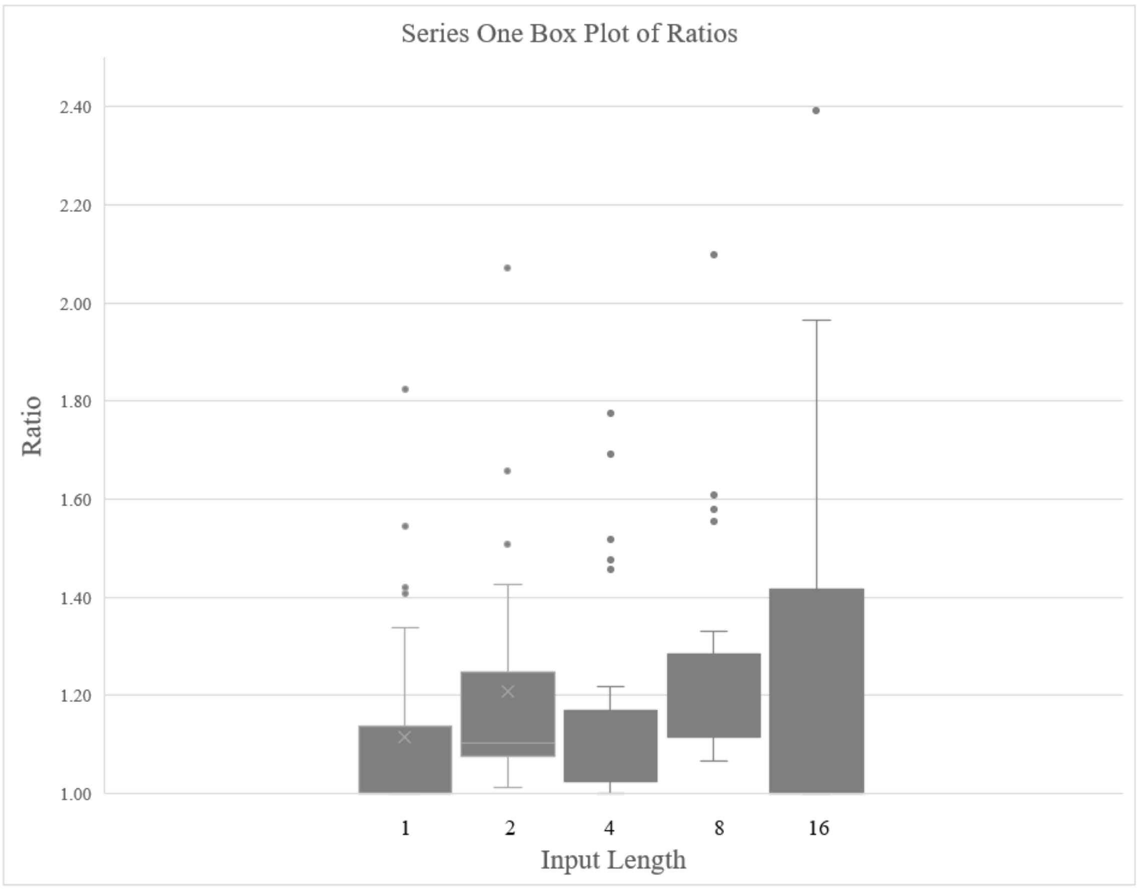


Figure 5.10: Box Plot of Series One Runtime Ratio

Table 5.5: Benchmark Timings - Series Two

Benchmark	Input Length				
	1	2	4	8	16
jxml2sql04	NS	NS	NS	NS	23244
jxml2sql07	NS	NS	NS	NS	22806
jxml2sql09	NS	NS	NS	NS	25735
jxml2sql14	NS	NS	NS	NS	2703
jxml2sql15	NS	NS	NS	NS	23633
jxml2sql16	NS	NS	NS	NS	27050
jxml2sql18	NS	NS	NS	NS	28037
jxml2sql19	NS	NS	NS	NS	24692
jxml2sql20	NS	NS	NS	NS	29204
jxml2sql21	NS	NS	NS	NS	24761
jxml2sql22	NS	NS	NS	NS	7274
jxml2sql23	NS	NS	NS	NS	27633
jxml2sql24	NS	NS	NS	NS	22717
jxml2sql25	NS	NS	NS	NS	25459
jxml2sql26	NS	NS	NS	NS	32534
jxml2sql27	NS	NS	NS	NS	26965
jxml2sql28	NS	NS	NS	NS	27434
jxml2sql29	NS	NS	NS	NS	31478
jxml2sql30	NS	NS	NS	NS	25518
jxml2sql31	NS	NS	NS	NS	25358
jxml2sql32	NS	NS	NS	NS	23804
jxml2sql33	NS	NS	NS	NS	22763
jxml2sql34	NS	NS	NS	NS	23770

NS = No solution found

Times in ms

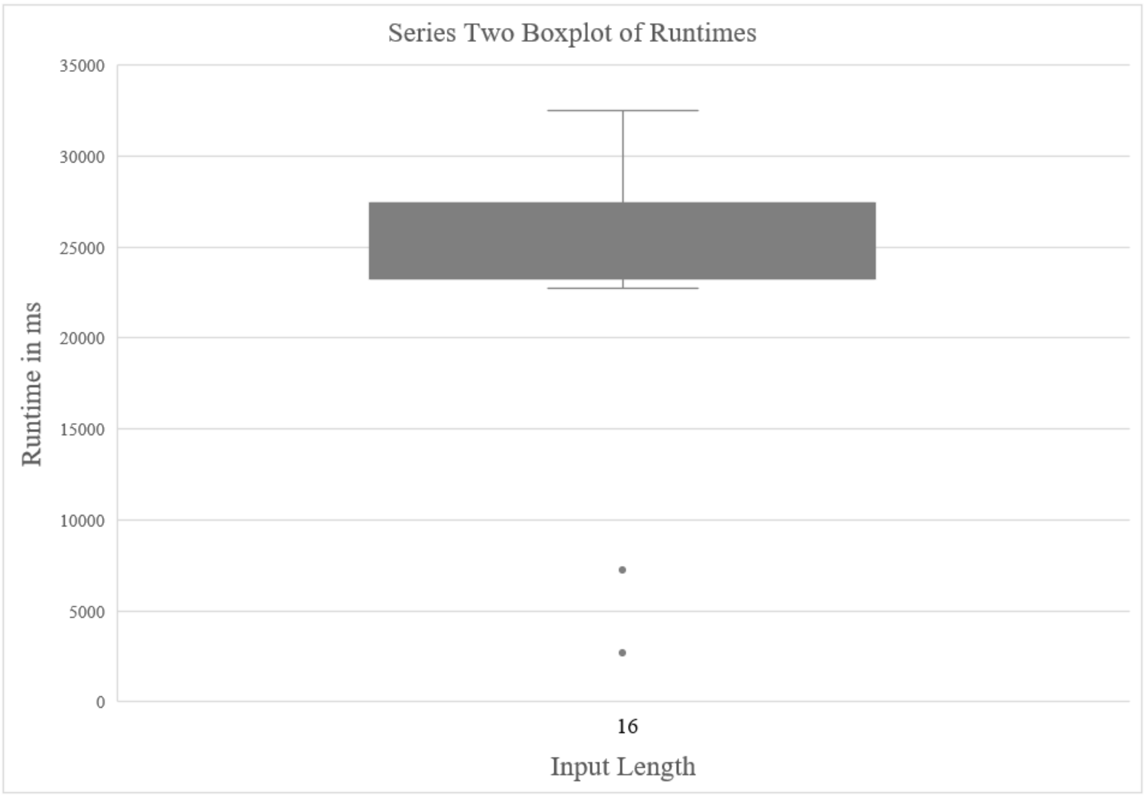


Figure 5.11: Box Plot of Series Two Runtimes

Table 5.6: Benchmark Timings - Series Three

Benchmark	Input Length				
	1	2	4	8	16
mathQuizGame01m	NS	NS	NS	68156	TO
mathQuizGame02m	NS	NS	NS	29541	TO
mathQuizGame03m	NS	NS	NS	99	97
mathQuizGame04m	NS	NS	NS	26625	TO
mathQuizGame09m	NS	NS	NS	107	TO
mathQuizGame10m	NS	NS	NS	707	1359154
mathQuizGame12m	NS	NS	NS	13908	TO
mathQuizGame13m	NS	NS	NS	142845	TO
mathQuizGame14m	NS	NS	NS	13538	TO
mathQuizGame15m	NS	NS	NS	144683	TO
mathQuizGame16m	NS	NS	NS	2731	TO
mathQuizGame17m	NS	NS	NS	20583	TO
mathQuizGame19m	NS	NS	NS	36783	TO
mathQuizGame20m	NS	NS	NS	533919	TO
mathQuizGame21m	NS	NS	NS	121021	TO
mathQuizGame22m	NS	NS	NS	204415	TO
mathQuizGame23m	NS	NS	NS	14178	TO
mathQuizGame24m	NS	NS	NS	45251	TO
mathQuizGame26m	NS	NS	NS	908959	TO
mathQuizGame27m	NS	NS	NS	137626	TO
mathQuizGame28m	NS	NS	NS	119110	TO
mathQuizGame29m	NS	NS	NS	198723	TO
mathQuizGame30m	NS	NS	NS	14072	TO
mathQuizGame31m	NS	NS	NS	56969	TO

NS	= No solution found
TO	= Timed out (>120m)

Times in ms

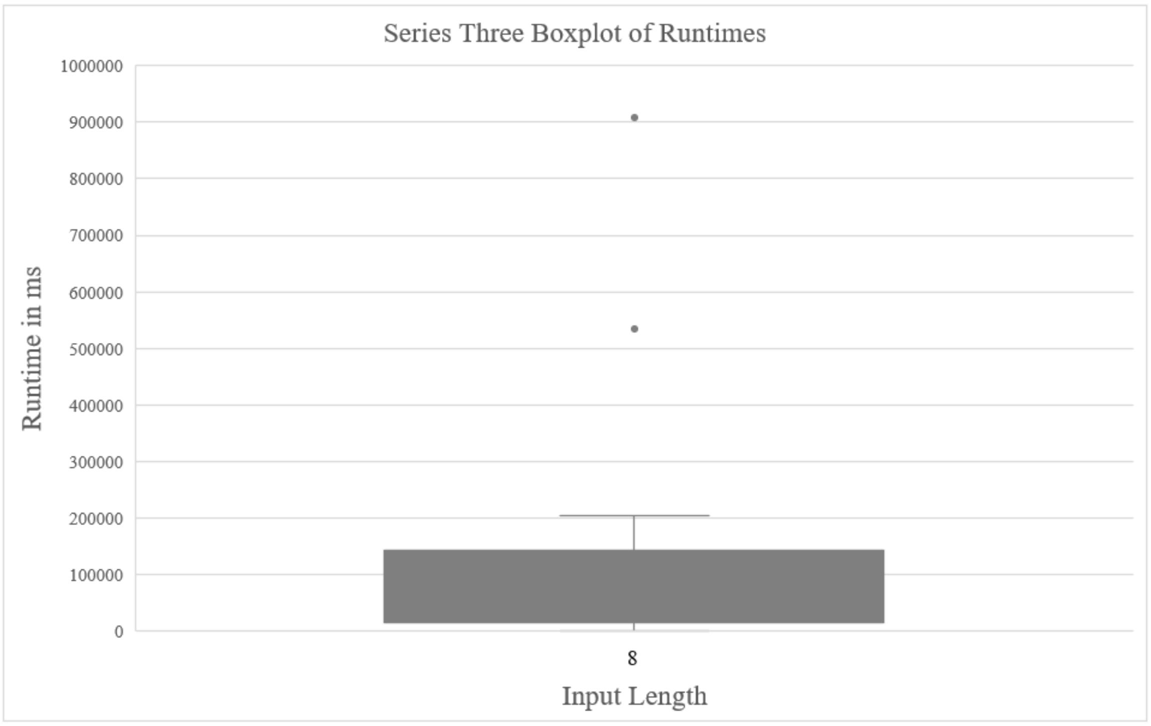


Figure 5.12: Box Plot of Series Three Runtimes

5.3 Scalability

In general, the solution is not scalable since solving string constraints is an undecidable problem [3]. The poor scalability results in the exponential growth in runtime vs. length of string input exhibited by several of the correctness benchmarks in Figure 5.13. However, when applied to real-world benchmarks, the resulting growth with increasing length is not as large, and in the case of benchmark series one, the longest length provided the fastest result in 13 out of 31 benchmarks.

The length of the symbolic string inputs is a primary factor in performance degradation, and thus scalability. All string operations in the solver operate on acyclic-automata. These automata are made up of states and transitions. As the length increases, so do the number of states and transitions in the underlying automata. And unlike undbounded or bounded-automata, acyclic-automata require at least one additional state and transition for each additional character of input. Thus, as length increases, so do the number of states and transitions that an operation must manipulate, leading to an increase in runtime.

Alphabet size is also a primary determinant in runtime. As the size of the alphabet increases, so do the number of transitions in the underlying automata, and the number of possible values for a given length increases with each additional alphabet symbol. Given an alphabet of size a and a length of symbolic input k the number of possible string values is a^k. This becomes problematic when the solver must find consistency in related values. Since the solver iteratively propagates single related value pairs, an increase the number of available pairs has a direct impact on runtime.

It may be possible to restrict the alphabet to only those symbols needed to sat-

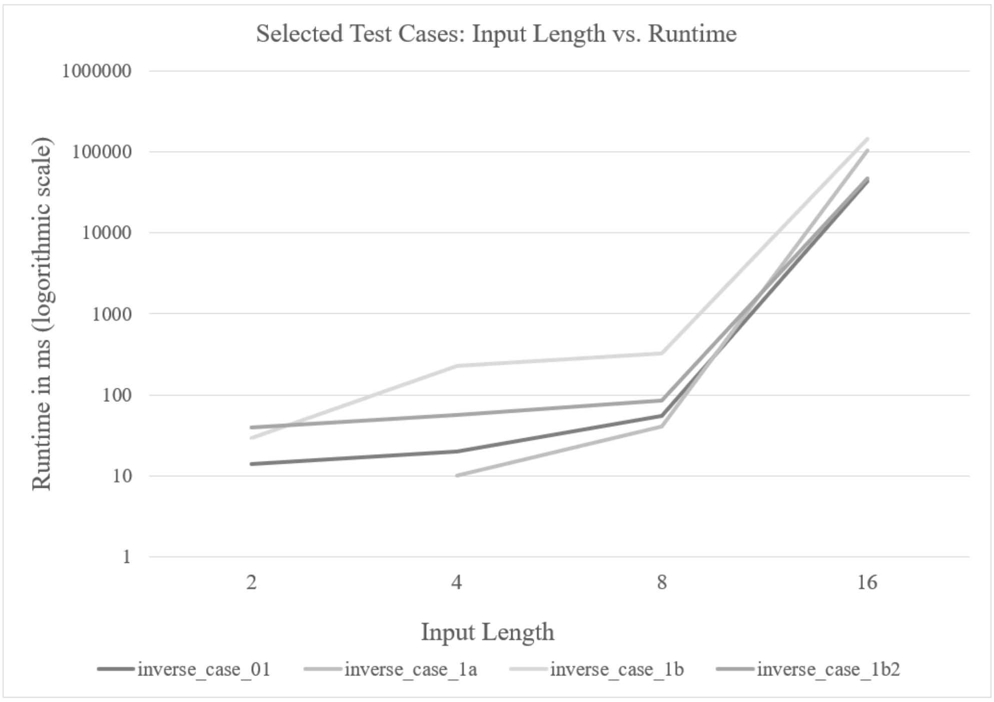


Figure 5.13: Growth in Runtime of Selected Test Cases

isfy path conditions. In particular, this would be of benefit when handling related values, as the solver would have fewer related pairs to generate and propagate. Table 5.7 shows the effect of adding a single uppercase and lowercase digit to the alphabet of test case 10ab. It is clear that limiting the alphabet to only those values necessary could improve the scalability of the solver.

Table 5.7: Effect of Alphabet Size on Test Case 10ab

Test Case	Time (ms)	Alphabet
inverse_case_10ab	48556	{A,B,C,a,b,c}
inverse_case_10ab	591335	{A,B,C,D,a,b,c,d}

5.4 Validity

There are several factors which may impact the external validity of this evaluation.

Restricted Alphabets Since runtime increases quadratically with increases in alphabet size, restricted alphabets are chosen as a default. Table 5.7 demonstrates runtimes quickly become large enough to make the evaluation impractical for certain test cases. However, extending the alphabet in test case 10ab does not affect the solution, only the time taken to achieve it.

Restricted Lengths Since runtime worsens with the increase in length, only experiments with lengths 1, 2, 4, 8 and 16 are evaluated. These appear to be adequate because the solver found solutions for synthetic and real-world benchmarks with at least one of these lengths. Further, once a length provides a feasible solution, longer lengths continue that trend. This would tend to indicate that once a minimum length has been determined, testing at longer lengths is unnecessary other than to provide additional analysis data or inputs of greater length.

Inability to Verify Solutions on Real-World Benchmarks The real-world benchmarks contained string operations that are not currently supported in SPF. Therefore the full testing sequence could not be performed on them at this time. This means we rely on the correctness benchmarks only to verify the correctness of the solver.

5.5 Summary

Experiments answer the research question of whether or not the solver is practical and effective. Data shows that the solver is practical because it finds string inputs for real-world programs benchmarks. The only circumstances in which the solver reports finding no solution are those in which the specified input length is too restrictive. Since the solver successfully generated solutions for real-world programs, it can be said that the solver is effective as well as practical.

The synthetic benchmarks proved to be a greater challenge than many of the benchmarks obtained from real-world programs. This suggests that the solver performance bottlenecks identified by the synthetic benchmarks may not be prevalent in real-world programs.

SECTION 6

CONCLUSION

This work demonstrates that an automata-based solver can be implemented for generating test inputs for real-world programs, both practically and efficiently. Symbolic Execution was examined in detail, along with possible automata types suitable for representing symbolic strings. Analysis shows the acyclic automata most suitable for our purposes. Novel inverse string operations on automata are presented which guarantee sound and complete results for a given string bound. In cases where the relationship between values must be maintained, this work demonstrates a novel method for ensuring them while keeping the automata model simple. Finally, the analysis of benchmark results shows that the solver is capable of producing correct results in the presence of non-injective and related-value string operations contained in real-world programs.

Future work should focus on the scalability of the solver. The solver currently generates input solutions based on a specified input length. This design choice is based on the need to have a finite input length in order to obtain solutions in a reasonable amount of time. However, as a practical matter, the length of inputs are generally not specified in Java programs other than they must be valid Java strings. Input solutions generated with smaller input sizes that reach a given location during program execution are as viable and usefull as those generated with longer input lengths.

Therefore, it may be beneficial to add a length decision heuristic in which the solver attempts to find a minimum length before starting, perhaps by examining predicate arguments and existing string operations in the constraint graph before starting forward analysis. It could then increase length incrementally in those cases where the chosen input length proves too restrictive to generate a solution.

Currently the solver is given an alphabet specification as part of the input. Since alphabet size is a significant factor in runtime, it may be beneficial to have an alphabet determination heuristic that determines a minimum viable alphabet based on the symbols found in concrete and argument values present in the constraint graph.

Finally, the solver cannot reliably process related predicates, such as embedded "If" statements. The algorithm should be extended to handle these conditions, possibly utilizing a breadth-first traversal of the TCG instead of depth-first.

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