Input Repair via Synthesis and Lightweight Error Feedback

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Abstract—Oftentimes, input data may ostensibly conform to a given input format, but cannot be parsed by a conforming program, for instance, due to human error or data corruption. In such cases, a data engineer is tasked with input repair, i.e., she has to manually repair the corrupt data such that it follows a given format, and hence can be processed by the conforming program. Such manual repair can be time-consuming and error-prone. In particular, input repair is challenging without an input specification (e.g., input grammar) or program analysis.

In this work, we show that incorporating lightweight failure feedback (e.g., input incompleteness) to parsers is sufficient to repair any corrupt input data with maximal closeness to the semantics of the input data. We propose an approach (called FSYNTH) that leverages lightweight error-feedback and input synthesis to repair invalid inputs. FSYNTH is grammar-agnostic and it does not require program analysis. Given a conforming program, and any invalid input, FSYNTH provides a set of repairs prioritized by the distance of the repair from the original input.

We evaluate FSYNTH on 806 (real-world) invalid inputs using four well-known input formats, namely INI, TinyC, SExp, and cJSON. In our evaluation, we found that FSYNTH recovers 91% of valid input data. FSYNTH is also highly effective and efficient in input repair; it repairs 77% of invalid inputs within four minutes. It is up to 35% more effective than DDMax, the previously best-known approach. Overall, our approach addresses several limitations of DDMax, both in terms of what it can repair, as well as in terms of the set of repairs offered.

I. INTRODUCTION

Input data is prone to unintended errors. Such errors may be introduced when the data is being created (by humans or by buggy programs), modified (by external actors) or transmitted (via flawed networks) [1]. For instance, several inputs are created by hand, leading to invalid inputs [2]. Invalid input data may also be caused by disagreements among data sources on the format specification which leads to different implementations of the specification. For example, JSON libraries implement slightly different definitions of the JSON formats [3], [4], different database systems support slightly different SQL formats [5], and various C compilers provide slightly different interpretation of the C language. These problems lead to invalid inputs that cannot be processed by their conforming programs or consumed by end-users (e.g., developers).

Given such invalid inputs that are almost but not quite parsable, developers are saddled with the task of input repair. Input repair is particularly important due to the high prevalence of invalid inputs in software practice [6]. It can be challenging to recover the valid portion of invalid inputs automatically [7], and developers often have to manually repair such inputs [6], which is time-consuming and error-prone.

Given a formal grammar for inputs, grammar-based input repair approaches such as error-correcting parsers [8]–[10], can repair invalid inputs. The main idea of such parsers is to generate a universal grammar that captures any mutation of the base grammar. Any parse of the input string that employs a mutation is penalized, and the parse with minimal mutation is chosen as the best parse, and the corresponding mutation the best repair. The limitation of this approach is that it assumes the existence of a formal grammar in the first place, which completely captures the intended structure. However, this assumption may not hold in practice due to several reasons. Firstly, certain input formats (e.g., URL standard from WHATWG [11]) may not have an official formal grammar specification. Even when the base grammar is context-free the tokenizer and deserializer may implement common subsets beyond the base grammar (e.g., comments and unquoted keys in JSON) which may contain important information. Hence, grammar-based input repair approaches are suboptimal for fixing invalid inputs in practice.

Black-box and language-agnostic input repair methods (e.g., lexical DDMax [6]) repair invalid inputs without a base grammar or program analysis. DDMax works similar to Delta Debugging [12], but in reverse. The idea is that given a corrupt input which induces a parse error, and a way to decompose the input into independent fragments (called deltas (δ)), one can successively minimize the parse-error inducing part of the input resulting in a maximal parsing input. Although DDMax works very well for most inputs, we observe it has certain limitations which inhibit it from completely repairing any invalid inputs. Table I and Section II illustrate these limitations with simplified invalid inputs. Notably, two major DDMax limitations include its (1) limited repair operation (only deletion), and (2) inability to completely repair rich input.
structures (e.g., multiple faults) due to inherent assumptions. Our approach addresses these limitations of DDMax, which we now discuss in detail.

Firstly, DDMax’s repair is restricted to deletion, which makes it sub-optimal for repairing some invalid inputs. While DDMax can repair invalid inputs due to spurious insertions, it fails to repair input invalidity that is due to changed or deleted fragments. Consider the sample invalid input in row one of Table 1 (i.e., \{"name": "Dave", "age": 42\}) which is invalid because of a missing comma separator between the two values in the JSON object. Due to the limited repair options of DDMax (i.e., only deletion), its resulting repair (i.e., \[42\]) is sub-optimal leading to a huge (75%) data loss (21 out of 28 bytes). This work addresses this challenge by supporting the synthesis of missing input fragments.

Secondly, DDMax is modeled after DDMin, where one of the unstated assumptions is that the \( \delta \) fragments that are not contributing to the failure observed can be independently removed without affecting the failure observed. When this assumption is not met, (i.e. where the inputs have a rich structure) the minimal fragment produced by DDMin can be sub-optimal. Similarly, DDMax assumes each non-failure-inducing fragment can be added to the passing subset without inducing a failure. When this assumption is not met (as in the case of inputs with a rich structure such as conforming to a grammar) the repairs produced can be suboptimal as the examples show. As an example, consider the invalid input in row three of Table 1 (i.e., \{"ABCD": \[1, 2, 3, 4, 5, 6\]\}). Due to the multiple faults (two \$s\) in this input, the resulting DDMax repair (i.e., \[123456\]) is sub-optimal causing a 77% data loss (20 out of 26 bytes).

This paper introduces the FSYNTH approach\(^1\) to address the limitations of DDMax via lightweight error-feedback and input synthesis. The key insight of this approach is to complete semantic repair of invalid inputs using lightweight failure feedback such as the validity, incompleteness, and incorrectness checks of input fragments. Given an invalid input and a conforming program, FSYNTH performs test experiments of input subsets and candidate insertions to provide a set of repairs prioritized by the distance of the repair from the original input. Unlike DDMax, FSYNTH does not have the implied assumption of independence of fragments. Hence, it does not face any limitation when given invalid inputs that should conform to a rich structure, and does not stumble when faced with multiple faults. Finally, it provides both deletion and synthesis as repair options making it an optimal algorithm in the toolbox of data engineers.

For instance, consider the invalid input in row one of Table 1 (i.e., \{"name": "Dave", "age": 42\}) which is invalid because of a missing comma separator between the two values in the JSON object. While DDMax could not completely repair this input, FSYNTH could complete a repair via input synthesis. Section \[\] describes the full steps of FSYNTH for this input. Specifically, FSYNTH first finds the maximal parsable prefix to be \{"name": "Dave", \} and determines that the parse boundary, i.e., the shift from incomplete to incorrect happens at boundary \{"name": "Dave", "age": 42\}. Next, FSYNTH applies deletion, or insertion of characters in order. In this case, the " is deleted first, but the resulting input \{"name": "Dave", "age": 42\} does not increase the maximum parsable prefix. Hence, FSYNTH next attempts to insert a character, eventually determining that only space characters and comma (,) can be inserted here, resulting in an increase of the maximal parse prefix. Out of these two insertion candidates, inserting comma results in the maximum advancement of the parse boundary, resulting in the valid repair: \{,"name": "Dave", "age": 42\}.

In this work, we show that invalid inputs with rich structure can be repaired adequately if the input processor can provide at least some indication of progress. That is, as with DDMax, we require the input processor to indicate if the input is valid. However, when given an invalid input, we require the input processor to indicate whether the input is merely incomplete (that is, the input is a prefix of a valid input) or is incorrect (that is, no suffix to this input will result in a valid input).\(^2\) We note that satisfying the requirements for FSYNTH does not require using a formal grammar for parsing, and indeed, there are several systems that implement handwritten parsers that satisfy FSYNTH constraints.\(^[14]\)

To the best of our knowledge, FSYNTH is the first approach to effectively repair invalid rich inputs without an input specification or program analysis. This paper makes the following contributions:

- **Repair via Input Synthesis.** FSYNTH expands the repository for input repair to deletion, insertion, and modification. Unlike DDMax, which is limited to deletion of input fragments, FSYNTH can repair errors due to omission.

- **Lightweight Failure Feedback.** FSYNTH is the first technique to demonstrate how to use lightweight parser-error-feedback (e.g., incomplete checks) for input repair.

- **Repairing Rich Input Structures.** We show that our FSYNTH technique can repair inputs with rich structure, including multiple faults and large spans. This is a major limitation of the state-of-the-art DDMax.

- **Empirical Evaluation.** We evaluate FSYNTH using 806 (real-world) invalid inputs belonging to four well-known input formats (e.g., cJSON and TinyC). Our evaluation results show that FSYNTH has a high (91\%) data recovery rate. It is up to 35\% more effective than DDMax.

The remainder of this paper is structured as follows: Section \[\] highlights the limitations of the state-of-the-art input repair method (DDMax) and illustrates how FSYNTH overcomes these limitations. In Section \[\] we describe how

\(^1\)FSYNTH denotes “Feedback-driven Input SYNTHeSis”

\(^2\)This requirement is provided by most parsers. In the cases where parsers do not provide this information, it can be obtained by external instrumentation as demonstrated by Björn et al.\(^[13]\), or by modifying the parser to provide such failure feedback, as demonstrated in this work.
TABLE I

DDMax vs. FSynth: examples showing limitations of DDMax and the strengths of FSynth

| Example | DDMax repair | FSynth repair | DDMax limitation |
|---------|--------------|---------------|-----------------|
| [ ] [ ] [ ] [ ] [ ] [ ] | [ ] [ ] [ ] [ ] [ ] [ ] | [ ] [ ] [ ] [ ] [ ] [ ] | Limited repair options (deletion) |
| [ ] [ ] [ ] [ ] [ ] [ ] | [ ] [ ] [ ] [ ] [ ] [ ] | [ ] [ ] [ ] [ ] [ ] [ ] | Rich structure (spans) |
| [ ] [ ] [ ] [ ] [ ] [ ] | [ ] [ ] [ ] [ ] [ ] [ ] | [ ] [ ] [ ] [ ] [ ] [ ] | Rich Structure (multiple-faults) |

FSynth conducts input synthesis, and Section [IV] describes the FSynth algorithm. We describe our experimental setup and findings in Section [V] and Section [VI]. We address the limitations of this work in Section [VII] and discuss related work in Section [VIII]. Finally, we conclude this paper with the discussion of future work in Section [IX].

II. Rich Input Structures

Let us illustrate the limitations of the state-of-the-art input repair method (DDMax) and how our approach (FSynth) addresses these limitations. Figure [I] provides a modified version of the lexical DDMax algorithm presented in Kirschner et al. [6]. A major limitation of lexical DDMax is that it results in sub-optimal repairs when the invalid input contains rich structures, e.g., multiple faults. In the following, we discuss these limitations.

A. Limitations due to multiple faults

A pattern of failure of DDMax occurs when DDMax is given an input with multiple errors. For example, consider the JSON input [ ] [ ] + . Here, the JSON string is invalid because of two invalid characters that are non-contiguous. The operation of DDMax (Figure [I]) proceeds as follows:

1) The operation starts with DDMax2(∅, 2)
2) |c* − ∅| ≠ 1. Hence, the base case does not apply
3) Increase to complement:
   c* − Δ1= [ ] +
   c* − Δ2= [ ]

4) Increase to subset:
   ∅ ∪ Δ1= [ ]
   ∅ ∪ Δ2= [ ]

5) Increase granularity: n < |c* − c'| which is 2 < |c* − ∅|
   Hence the next iteration is: DDMax2(∅, 4)
6) |c* − ∅| ≠ 1. Hence, the base case does not apply.
7) Increase to complement:
   c* − Δ1= [ ] +
   c* − Δ2= [ ]
   c* − Δ3= [ ]
   c* − Δ4= [ ]

8) Increase to subset:
   ∅ ∪ Δ1= [ ]
   ∅ ∪ Δ2= [ ]
   ∅ ∪ Δ3= [ ]
   ∅ ∪ Δ4= [ ]

9) Increase granularity: 4 < 4
10) The solution is ∅.

That is, DDMax is unable to optimally repair inputs of this kind which contains multiple errors. While in this example, the data loss that occurred may seem somewhat limited, this need not always be the case. A similar example is given in Table [I]. Here, [ ] [ ] [ ] [ ] [ ] [ ] [ ] [ ] contains two distinct corruptions. As in the previous case, DDMax attempts to fix this input by dividing it into smaller and smaller fragments, none of which isolates an error that when removed, results in the solution 1 2 3 4 5 6 with significant data loss, including the loss of structure and change in input fragment type from string to number. Hence, DDMax cannot effectively repair inputs containing multiple faults.

B. Effect of input decomposition

Unfortunately DDMax can produce non-optimal results even when the errors are contiguous, and hence considered single by DDMax. The problem happens when the corruption in the input interacts with the fragment decomposition algorithm of DDMax. As an example, consider a variant of the previous input: [ ] [ ] + . The JSON string is invalid here because it contains two invalid characters which are contiguous. The operation of DDMax (Figure [I]) is as follows:

1) The operation starts with DDMax2(∅, 2)
2) |c* − ∅| ≠ 1. Hence, the base case does not apply
3) Increase to complement:
   c* − Δ1= [ ] +
   c* − Δ2= [ ]

4) Increase to subset:
   ∅ ∪ Δ1= [ ]
   ∅ ∪ Δ2= [ ]

5) Increase granularity: n < |c* − c'| which is 2 < |c* − ∅|
   Hence the next iteration is: DDMax2(∅, 4)
6) |c* − ∅| ≠ 1. Hence, the base case does not apply.
7) Increase to complement:
   c* − Δ1= [ ] +
   c* − Δ2= [ ]
   c* − Δ3= [ ]
   c* − Δ4= [ ]

8) Increase to subset:
   ∅ ∪ Δ1= [ ]
   ∅ ∪ Δ2= [ ]
Maximizing Delta Debugging Algorithm

Let \( \text{test} \) and \( c_x \) be given such that \( \text{test}(\emptyset) = \checkmark \wedge \text{test}(c_x) = \times \) hold. The goal is to find \( c'_x = \text{DDMax}(c_x) \) such that \( c'_x \subseteq c_x \), \( \text{test}(c'_x) = \checkmark \), and \( \Delta = c_x - c'_x \) is 1-minimal. The maximizong Delta Debugging algorithm \( \text{DDMax}(c) \) is

\[
\text{DDMax}(c_x) = \text{DDMax}_2(\emptyset, 2) \quad \text{where} \quad \begin{cases} c'_x & \text{if } |c_x - c'_x| = 1 \text{ ("base case")}, \\ \text{DDMax}_2(c_x - \Delta_i, 2) & \text{else if } \exists i \in \{1, \ldots, n\} \cdot \text{test}(c_x - \Delta_i) = \checkmark \text{ ("increase to complement")}, \\ \text{DDMax}_2(c'_x \cup \Delta_i, \max(n - 1, 2)) & \text{else if } \exists i \in \{1, \ldots, n\} \cdot \text{test}(c'_x \cup \Delta_i) = \checkmark \text{ ("increase subset")}, \\ \text{DDMax}_2(c'_x, \min(|c_x - c'_x|, 2n)) & \text{else if } n < |c_x - c'_x| \text{ ("increase granularity")}, \\ c'_x & \text{otherwise ("done")}. \end{cases}
\]

where \( \Delta = c_x - c'_x = \Delta_1 \cup \Delta_2 \cup \cdots \cup \Delta_n \), all \( \Delta_i \) are pairwise disjoint, and \( \forall \Delta_i : |\Delta_i| \approx |c_x - c'_x|/n \) holds. The recursion invariant (and thus precondition) for \( \text{DDMax}_2 \) is \( \text{test}(c'_x) = \checkmark \wedge n \leq |\Delta| \).

a: Bugfix: This base case is necessary to ensure that repairing JSON input \( \{\*\*\*\*\*\} \) does not violate the invariant \( n \leq |\Delta| \).

b: Bugfix: We should look for minimum of the remaining so that invariant \( n \leq |\Delta| \) is not violated for JSON input \( \{\*\*\*\*\*\} \).

Fig. 1. Modified Maximizing Lexical Debugging algorithm, extended from Kirschner et al. [6]

9) Increase granularity: \( 4 < 4 \times \)

10) The solution is \( \emptyset \).

That is, this particular invalid JSON string also cannot be repaired by \( \text{DDMax} \). As in the previous case, the data loss can be severe. Consider \{ "item": "Apple", "price": \*\*\*3.45 \} in Table[1], which is similar to Kirchner et al. [6] Figure 1] but with an extra *. \( \text{DDMax} \) repairs this input to \*\*\*\*\*3.45\*, resulting in data loss.

The problem here is that the successive partitions attempted by \( \text{DDMax} \) fails to isolate the failure causing fragment even though the fragment is contiguous. That is, no single independent fragment is found, the removal of which results in removal of the error. Hence, \( \text{DDMax} \) keeps searching for smaller and smaller fragments discarding larger and larger chunks of data.

C. Discussion

Why does \( \text{DDMax} \) fail to repair these inputs? A major limitation of \( \text{DDMax} \) is that it is modeled on DDMin, which is an effective tool for minimization of failure inducing inputs. Given a failure inducing input, the idea of DDMin is to successively partition the input into smaller and smaller chunks, remove one chunk at a time and check whether the remaining chunks are sufficient to reproduce the failure. As this implies, a key assumption of DDMin is that we can actually remove such chunks independently. That is, if a chunk does not contribute to the observed failure, it can be removed without affecting the failure observed. Secondly, if multiple chunks independently cause the same failure, only one chunk will be chosen, and minimized further.

The definition of \( \text{DDMax} \) is a mirror of DDMin. \( \text{DDMax} \) starts with an empty input that is assumed to be passing. Then, it partitions the input into chunks, and tries to concatenate any of these chunks to the passing input, producing a larger passing input. If after dividing the input into \( n \) chunks, none of the chunks could produce a passing input, it tries again by dividing the input into \( 2n \) chunks.

As in the case of DDMin, the unstated assumption here is that if a chunk was not responsible for the observed failure, it can be extracted independently of other chunks and added to the passing input fragment without changing the semantics. This particular assumption need not hold when we are dealing with inputs that have a rich structure. That is, \( \{\*\*\*2, 3, 4, 5\} \) is very different from \( 12345 \) even though a significant portion of the raw characters from first is preserved in the second. Further, once such a semantically changed fragment forms the seed of the passing fragment, due to the constraints in the input structure, the remaining fragments from the original will likely not combine with the seed fragment, resulting in further data loss.

Although \( \text{DDMax} \) will have no problems maximizing any inputs if the input processor conforms to this constraint, we note that this can be a rather strong constraint in practice.

D. Updates to \( \text{DDMax} \) definition

While evaluating \( \text{DDMax} \), we noticed two cases where the formal definition of \( \text{DDMax} \) was underspecified. These are noted in Figure[1]. Specifically, (1) \( \text{DDMax} \) requires the base case when \( |c_x - c'_x| = 1 \). If not, \( \text{DDMax} \) can go into unbounded recursion on inputs such as the JSON input: \( \{1^\*1\} \). (2) when increasing granularity, the size of the remaining input should be considered rather than the size of the entire text. Not
doing this would cause an invariant fail for inputs such as
\{ "m": 2 \}.

E. Repair of rich inputs with FSYNTH

One of the strengths of FSYNTH is that it can effectively handle inputs with rich structure. Consider the input to the JSON processor: \{ "ABCD" : [1, 2, 3, 4, 5, 6] \}.
(For ease of explanation, let us consider only deletion as the operation used.) Here, the procedure is as follows:

1) FSYNTH starts by executing a binary search for the boundary where the input prefix changes from incomplete to incorrect. This is obtained at index 10, providing the incomplete substring \{ "ABCD" : [1, 2, 3, 4, 5, 6] \}.

2) FSYNTH then appends the next character \( m \) to the input, resulting in \{ "ABCD" : [1, 2, 3, 4, 5, 6, m] \} and observes the result. In this case, the JSON processor returns incorrect.

3) Hence, the newly added character is discarded, and the character at the next index is appended, resulting in \{ "ABCD" : [1, 2, 3, 4, 5] \}. This results in JSON processor responding incomplete.

4) FSYNTH now appends the character in the next index, resulting in \{ "ABCD" : [1, 2, 3, 4] \} which again results in incomplete from JSON processor.

5) Proceeding in this fashion the input reaches \{ "ABCD" : [1, 2, 3, 4, 5, 6] \} at which point, we again have the response incorrect from the JSON processor. Hence, we discard this character, and try the next character, resulting in \{ "ABCD" : [1, 2, 3, 4, 5, 6] \}.

6) The JSON processor responds with complete.

This completes the repair of the given input. This demonstrates that FSYNTH has no problem repairing rich inputs containing multiple errors.

III. INPUT SYNTHESIS

The second major limitation of DDMax is that the only operation in its toolbox is deletion of input fragments. Consider
\{ "name" : "Dave", "age" : 42 \} Here, there is a missing quote in the key. DDMax repair of this string will result in "Dave" age: 42. The problem is that deletion of fragments alone can lead to significant corruption of information. In this instance, the availability of insertion could have repaired the input string to
\{ "name" : "Dave", "age" : 42 \}.

Unfortunately, because DDMax is unable to synthesize any fragments, opportunities for repair can be missed.

The FSYNTH algorithm on the other hand, follows in this fashion.

1) FSYNTH algorithm starts with the corrupted input and quickly finds the maximal parsable prefix using a binary search:
\{ "name" : "Dave" \}.

2) At this point, FSYNTH applies deletion, insertion, or modification of characters in order. In this case, the \( m \) is deleted first, resulting in:
\{ "name" : "Dave" | age" : 42 \}.

3) The JSON parser responds with incorrect for this input.

4) FSYNTH next attempts to insert a character. Say we tried to insert \( S \). This results in:
\{ "name" : "Dave" | "age" : 42 \}.

5) The JSON parser responds with incorrect for this input.

6) Indeed, only space characters and comma (\( , \)) can be inserted here, resulting in incomplete from the JSON parser.

7) Inserting the \( , \) results in a new input:
\{ "name" : "Dave", "age" : 42 \}.

8) This is accepted as a valid repair.

That is, the ability of FSYNTH to synthesize characters for repair can lead to more effective repairs.

IV. FSYNTH

The main strength of FSYNTH is its repertoire of repairs. The input string can be modified by deleting any character (Listing [1]), or inserting a character at any index (Listing [1]). In the listings below, Repair is a tuple that allows accessing its first argument with inputstr and its second argument with boundary.

We define a few terms before we start:
valid substring. The valid substring of a string is the maximal prefix where the parser returns incomplete.
boundary. The boundary or parse boundary is the index of the first character after the valid substring that results in incorrect response from the parser, or one past the end if the input is incomplete.
repair. A repair is a single modification (deletion or insertion of a single character) made on an input string.
repair thread. A repair thread is a set of repairs made on an input string. A repair thread has a single boundary and a corresponding valid prefix.

The deletion algorithm is simple. When a parse error is observed, the character that caused the error is present at the boundary value. That is, we know that inputstr[ : boundary] parses correctly. Hence, for deletion, we produce a string without the character at the boundary.

Listing 1. FSYNTH repairs

```python
1  def apply_delete(item):
2     inp = item.inputstr[ : item.boundary] +
3     item.inputstr[item.boundary + 1 :]
4  return extend_deleted_item(Repair(inp, item.boundary))
```

For insertion, the algorithm is more involved. The problem is that we need to handle corruption in inputs such as "12345mystring" which is used as input to a JSON parser. Consider what happens when the first quote is deleted. In this case, we will get the first parse error at m. But plainly, the best repair is before the first parse error. The problem is that insertions at random points in the prefix is very costly, resulting in \( |\alpha| \times |S| \) modifications where \( |\alpha| \) is the number of alphabets (characters) the language has, and \( |S| \) is the length

\( |S| \) is the length of the input string.
of the prefix. Hence, we allow the user to choose to toggle this option with LAST_INSERT_ONLY. If the option is false, we will attempt repairs at any point in the prefix. If it is true, we will only attempt insertions at the end of the prefix.

Listing 2. FSynth repairs

```python
1 def insert_at(item, k, i, suffix):
2     v = item.insert_char(k, i, suffix)
3     if v is None: return None
4     new_item = Repair(v, k, mask='{}_I%d' % item.mask)
5     ie = extend_inserted_item(new_item)
6     if ie.boundary > k:
7         return ie
8     return None
9
10 def apply_insert(item):
11     return_lst = []
12     if LAST_INSERT_ONLY:
13         return_lst = []
14     for k in range(item.boundary):
15         v = insert_at(item, k, i, suffix)
16         if v is None: return_lst.append(v)
17     if not inputstr: return left
18     middle = (left + right) // 2
19     while left + 1 < right:
20         if is_incomplete(Repair(inputstr, middle)):  
21             left = middle
22         else:
23             right = middle
24     return left
25
26 def binary_search(inputstr, left=0, right=len(inputstr)-1):
27     if not inputstr: return left
28     if is_incomplete(Repair(inputstr, right)):  
29         return len(inputstr)-1
30     while left + 1 < right:
31         middle = (left + right) // 2
32         if is_incomplete(Repair(inputstr, middle)):  
33             left = middle
34         else:
35             right = middle
36     return left
```

The function `find_fixes()` takes in the input string and the parse boundary. It then generates a set of repair threads, out of which a few are chosen for continuation (Listing 6). Then, each repair thread is processed individually. On each thread, a set of repairs (Listing 1, Listing 2) are applied. If the repair succeeds, the string can use more characters from the pending suffix resulting in a larger valid prefix string, but with a larger edit distance. This procedure is repeated until the prefix string is marked complete by the input processor.

The sampling procedure attempts to discard redundant repairs so that the number of simultaneous threads we have to maintain does not grow unbounded. While doing that, it ensures that no unique repairs are discarded. For example, given a JSON fragment \([1,2\{a\{repair of \([1,2,3], [1,24\) and \([1,25\) are redundant but \([1,2,3\), is unique because the last repair represents a change in semantics for the parser. The key insight here is to look at the extension of a given string to classify whether it is unique or not. That is, given a string \([1,2,\text{"x"}]\), after repair of \([1,2,\text{"x"}],\) the next extension of the string is likely to be a comma or a digit insertion. However, after \([1,2,3\), the pending suffix can be used to extend the string resulting in \([1,2,\text{"x"}]\). Hence, we use the kind of repairs conducted on a string, the length of the prefix, as well as the last character added as the uniqueness indicator.

Unfortunately, using all repairs even after eliminating all redundant repairs can be rather time consuming. If this is the case, one can limit the repair threads to the best performing ones in terms of the parse boundary by using `filter_best()`.

Listing 3 shows how FSynth is invoked. The input string is passed to repair().

Listing 3. FSynth initial search

```python
1 def repair(inp):
2     boundary = binary_search(inp)
3     return find_fixes(inp, boundary)
```

This function does a binary search (Listing 4) on the argument string looking for the parse boundary where the return value changes from incomplete to incorrect. That is, if binary_search returns an index \(n\), then `inputstr[:n]` is a valid prefix, and `inputstr[n:]` is the error causing character if one exists or the `inputstr` is incomplete.

Listing 4. Binary search

```python
1 def binary_search(inputstr, left=0, right=len(inputstr)-1):
2     if not inputstr: return left
3     if is_incomplete(Repair(inputstr, right)):  
4         return len(inputstr)-1
5     while left + 1 < right:
6         middle = (left + right) // 2
7         if is_incomplete(Repair(inputstr, middle)):  
8             left = middle
9         else:
10             right = middle
11     return left
```

The boundary value is then passed to `find_fixes()` (Listing 5).

Listing 5. Find fixes

```python
1 def find_fixes(inputval, boundary):
2     next_items = [Repair(inputval, boundary)]
3     while True:
4         current_items, next_items = next_items, []
5         completed = []
6         for item in sample_items_by_mask(current_items):
7             if i.is_complete(): completed.append(i)
8             if completed: return completed
9             for i in repair_and_extend(item)
10             next_items.append(i)
11             if len(masks[key]) < MAX_NUM_PER_MASK:
12                 sampled = []
13                 for key in masks:
14                     if len(masks[key]) > MAX_NUM_PER_MASK:
15                         res = random.sample(masks[key], MAX_NUM_PER_MASK)
16                     else:
17                         res = random.sample(masks[key], 1)
18                     sampled.extend(res)
19                 return filter_best(sampled)
20     for item in current_items:
21         if item.is_complete(): completed.append(item)
22     return completed
23     return filter_best(sampled)
```

After each repair, the new string is checked to see if the string results in incomplete rather than incorrect. If the string is
results in incomplete, a new parse boundary is found by repeatedly extending the string with a pending character from the remaining suffix in the input string. The small complication here is that different search algorithms are more suitable for deletion and insertion. With deletion, we have removed the error causing character, so the next parse error may be far away. Hence, we use binary search to find the next parse error (Listing 7).

Listing 7. Extend the boundary

```python
def extend_deleted_item(item):
    return bsearch_extend_item(item)

def bsearch_extend_item(item):
    bs = binary_search(item.inputstr, left=item.boundary)
    item.boundary = bs
    return item
```

In the case of insert, however, in most cases, the character being inserted, and the character that originally caused a parse error can still cause a parse error. Hence, we apply linear search instead (Listing 8).

Listing 8. Extend the boundary

```python
def extend_inserted_item(item):
    return lsearch_extend_item(item, nxt=1)

def lsearch_extend_item(item, nxt=1):
    while True:
        if (item.boundary + nxt) > len(item.inputstr):
            item.boundary = item.boundary + nxt - 1
            return item
        s = Repair(item.inputstr, item.boundary + nxt)
        if is_incorrect(s):
            nxt += 1
            continue
        if is_incorrect(s):
            item.boundary = item.boundary + nxt - 1
            return item
```

If this succeeds, the parse boundary after the repair would be larger than the old parse boundary. Hence, if the parse boundary has increased (Listing 9), then the repair is saved. If not, the repair is discarded.

Listing 9. Repair and extend

```python
def repair_and_extend(item):
    return [apply_delete(item)] + apply_insert(item)
```

The output from find_fixes() (Listing 5) is a set of repair threads with the least number of repairs from the passed input string.

FSYNTH assumes the parser correctly signals incomplete for incomplete inputs, incorrect for other invalid inputs, and complete if the input was valid. Given this, FSYNTH algorithm works as follows (Figure 2):

1) Binary search. Given any corrupt input, FSYNTH starts by a binary search of the input to determine the parse boundary. This then is used to construct the first repair thread, with boundary set to the binary search result, and repairs set to empty.

2) Repair. Starting with any existing repair thread, FSYNTH applies deletion and insertion repairs. A single deletion results in a single repair thread which is an extension of the original repair thread. An insertion however, results in multiple repair threads corresponding to the number of characters.

3) Extension. For each thread that results from repair, extend the thread until the new parse boundary. For threads resulting from insertion, keep only those threads that results in a different parse boundary from the old.

4) Selection. We remove any redundant repair threads, and choose the best threads if a selection criterion is supplied.

5) Final Fix. We then iteratively choose each thread and continue making repairs until the parser output at the boundary changes from incomplete to complete.

The output of the algorithm is a set of repair threads each of which fixes the input using a set of repairs. The repair threads are sorted in the order of least number of repairs required to fix the input.

V. EXPERIMENTAL SETUP

This section describes the experimental setup of this work. Research Questions: We investigate the data recovery (RQ1), effectiveness (RQ2), and efficiency (RQ3) of our approach using several well-designed experiments. We also examine how
FSYNTH compares to four state-of-the-art techniques, namely the built-in repair of the programs (baseline), error-recovery of ANTLR, as well as lexical DDMAX and syntactic DDMAX. Specifically, we pose the following research questions:

**RQ1: Data Recovery and Data Loss.** How much input data is recovered by FSYNTH, and how much data is lost? Does FSYNTH recover as much data as the state-of-the-art methods?

**RQ2: Effectiveness.** How effective is FSYNTH in fixing invalid inputs? Is it as effective as the state-of-the-art methods?

**RQ3: Efficiency.** What is the efficiency (runtime) of FSYNTH? Is it as efficient as the state-of-the-art techniques?

**Subject Programs:** We used four input formats and their corresponding programs. These are ANTLR (IN), JSON (cJSON), S-Expressions (SExpParser) and TinyC (TinyC). Each program is moderately large (between 375 LOC to 3062 LOC), relatively mature (6 to 21 years old), and written in C. Further details are provided in Table II.

**Test inputs:** Table III provides details of the number of real-world invalid inputs and mutated invalid inputs employed in our experiment. We evaluate our approach using 806 invalid input files. As test inputs, we crawled a large corpus of valid and invalid real-world files from GitHub using the GitHub crawling API [13]. In addition to real invalid inputs, for each format, we introduced a set of 100 artifically mutated (invalid) files from 50 randomly selected valid real-world files. Half of those mutated files contain a single mutated byte and the other half contains multiple (two to 16) mutated bytes. Each mutation can either be a byte-flip, an insertion or a deletion to resemble real-world corruptions as close as possible (e.g., bit rot on hard disks or transmission errors in network protocols).

**Metrics and Measures:** We employ the following metrics and measures to evaluate repair quality:

1. **Number of Repaired Inputs:** We count the number of files repaired before a four minute timeout for each repair method.
2. **File Size Difference:** To determine the amount of data recovered by each approach, we evaluate the difference in file size of the recovered inputs and the original valid input.
3. **Edit Distance:** This is measured as the number of characters that differs between the corrupt input and the repaired input.
4. **Runtime:** The time taken for input repair for each method.
5. **Number of Program Runs:** To evaluate efficiency, we track the number of times the parser is executed by each approach.

**State-of-the-art:** In this work, we compare the performance of FSYNTH to the following techniques: (1) **Baseline:** The built-in error-recovery technique of the subject programs. (2) **ANTLR:** This is the inbuilt error recovery strategy of the ANTLR parser generator when equipped with an input grammar specifying the allowed input structure. (3) **DDMAX:** Kirschner et al. proposed two variants of the maximizing variant of the delta debugging algorithm (called DDMAX), namely lexical DDMAX and syntactic DDMAX.

**Implementation Details:** We implemented the test infrastructure in about 12k LOC of Java code, FSYNTH was implemented in 765 lines of Java code. We also slightly modify subject programs to provide the required incompleteness feedback (see Table I).

**Platform:** All experiments were conducted on an ASRock X470D4U with six physical CPU cores and 32GB of RAM, with an AMD Ryzen 5600X @ 3.70GHz, 12 virtual cores, running Debian GNU/Linux.

**Research Protocol:** We first collect a large corpus of real-world files which we split into a set of (50) valid files and invalid files. We create additional mutated invalid files by injecting single and up to 16 multiple mutations (random insertions, deletions and byte-flips) into the valid files (Table III). Then, we run each repair technique on each file and collect the required data, i.e. the run time, number of oracle runs, Levenshtein distance and repair status of each file. As repair techniques, we employ Baseline, ANTLR, lexical DDMAX, syntactic DDMAX and FSYNTH. All experiments were conducted within a timeout of four minutes per input, for each repair technique. The maximum time budget was empirically determined in our preliminary experiments to ensure a balanced evaluation for all techniques. We found that four minutes is a sufficient time budget to evaluate all techniques on most inputs. It is also a reasonable maximum repair time for an end-user. In our experiments, a longer timeout did not result in a significant increase in repairs for all techniques.

VI. EXPERIMENTAL RESULTS

This section discusses the results of our experiments.

**RQ1 Data Recovery and Data Loss:** Let us investigate the amount of data recovered and lost by FSYNTH, in comparison to the best-performing state-of-the-art method (DDMAX).

**Data Recovery:** We examine 474 inputs that were completely repaired by lexical DDMAX, syntactic DDMAX and FSYNTH,
excluding empty files (and white spaces). Table [V] highlights the amount of data recovered and lost by each approach.

Results show that FSynth has a very high data recovery rate. It recovered 91% of input data, on average. This is 23% more than the most effective baseline (syntactic DDMax). For all input formats, FSynth recovered up to (75%) more data than both variants of DDMax. Consider TinyC, where FSynth recovered up to 75% more input data than DDMax (see Table [IV]). These results show that FSynth is more effective in recovering valid input data than DDMax.

**Data Loss:** To measure data loss, we compute the Levenshtein distance between repaired and invalid files using 327 completely repaired inputs where edit distance could be computed within a threshold of 750 edit distances (about 30 seconds).

We found that FSynth achieves a low data loss of about 11 edit distances, on average, which is up to 10 times lower than (syntactic) DDMax. Table [IV] shows that for almost all input formats, FSynth achieved a lower data loss than syntactic and lexical DDMax (except for SExp). This better performance is attributed to the lightweight failure feedback of FSynth, which allows it to distinguish between incomplete and incorrect input fragments.

**RQ2 Effectiveness:** In this experiment, we measure the total number of files repaired by our approach. In addition, we compare the performance of FSynth to four state-of-the-art methods containing both language-agnostic input repair approaches and grammar-based input repair techniques. Language-agnostic input repair approaches include the built-in error-recovery of the subject program (called baseline) and lexical ddmax (see Table [V]). For comparison to grammar-based input repair methods, we employ the built-in error-recovery strategy of the ANTLR parser generator, and syntactic ddmax (see Table [VI]).

**Figure 3** also highlights the effectiveness of FSynth in contrast to the state-of-the-art methods.

**Repair Effectiveness:** Our approach is very effective in repairing invalid inputs, it repaired almost four out of every five invalid input within a four minute timeout, i.e., about 77% (624 out of 806) of invalid inputs. In comparison to language-agnostic approaches, FSynth is up to 18 times more effective than the built-in error recovery strategy of the subject programs (33 vs. 624 repairs), and up to 35% more effective than the best performing language-agnostic approach for certain input formats (cJSON and TinyC). Overall, Table [V] shows that FSynth is eight percent more effective than the best language-agnostic repair technique (i.e., lexical DDMax). Additionally, results show that FSynth outperforms the grammar-based input repair approaches by up to 28%. Despite zero knowledge of the input format, Table [VI] shows that our approach outperformed the grammar-based input repair approaches: FSynth is almost twice as effective as the error-recovery strategy of ANTLR (see Figure 3), and slightly (2%) more effective than the best-performing grammar-based approach (i.e., syntactic DDMax). The effectiveness of syntactic DDMax is due to its knowledge of the input grammar. These results suggest that the combination of failure feedback and input synthesis is vital for the effective repair of invalid inputs.

**FSynth is very effective in repairing invalid input files:** It repaired four out of five (77%) of invalid inputs and it is 8% more effective than the best language-agnostic method (lexical DDMax).

**Complementarity to DDMax:** We further inspect the unique repairs achieved by each approach to understand the complementarity of our approach to the state-of-the-art methods. In this experiment, we inspect the number of unique repairs achieved solely by a single approach (e.g., only FSynth), or two or more approaches (e.g., all approaches). Figure 4 highlights our findings.

We found that about one in ten repairs could be solely completed by FSynth, which is three times and five times as many as lexical and syntactic DDMax repairs, respectively (see Figure 4). FSynth solely completed 9% (61/712) of all repaired inputs, all of which DDMax could not repair. For lexical DDMax, our approach solely repaired 5× as many invalid files as lexical DDMax (61 vs. 12), while it repairs thrice as many files as syntactic DDMax (DDMaxG) (61 vs. 23). Overall, we observe that FSynth complements DDMax.

---

3 Note that due to input synthesis (i.e., insertion of input elements), FSynth may report recovering more than 100% of the input file (e.g., 100.6% for SExp in Table [IV]).
a combination of these approaches completes 88% of repairs (712), which is 14% and 23% more than the repairs completed solely by FSYNT or syntactic DDMax, respectively. On inspection, we found that the types of repairs completed by FSYNT (but not by DDMax) were mostly insertions. We found that the insertions performed by FSYNT were mostly (missing) syntactic elements of the input like curly braces and colons for JSON or line breaks for INI. In some cases, FSYNT inserted alphanumeric characters. For instance, if a grammar expects a char where there is a missing char. Overall, we attribute the unique repair achieved by FSYNT to the synergistic combination of failure feedback and input synthesis.

**RQ3 Efficiency:** Let us evaluate the time performance of our approach. For a balanced evaluation, we analyse a set of 480 invalid inputs that were completely repaired by all three approaches within the four minutes timeout, without data collection and experimental analysis time. Table VII reports the efficiency of all three approaches.

**FSYNT is considerably efficient in input repair:** It is reasonably fast, it takes about 10 seconds to repair an invalid input, on average. However, it is about five times slower than DDMax (two to three seconds, on average). Table VII shows that the execution time of FSYNT is much higher than that of syntactic and lexical DDMax. This result is due to the number of program runs required by FSYNT, especially due to its additional repair operation (input synthesis) and its extra oracle checks (incompleteness and parser boundary). FSYNT is reasonably efficient, similar to DDMax, the number of program runs is its main performance bottleneck.

**FSYNT is reasonably fast (10 seconds), but it is 5× slower than DDMax because it requires additional operations and oracle checks.**

**VII. LIMITATIONS AND THREATS TO VALIDITY**

Our approach (FSYNT) and empirical evaluations may be limited by the following:

**External Validity:** This refers to the generalizability of our approach, i.e., the threat that FSYNT may not generalize to other programs and input formats. To mitigate this threat, we have employed four well-known input formats with varying complexity, their corresponding programs also have varying sizes (375 to 3062 LOC) and maturity (6 to 21 years old).

**Internal Validity:** This concerns the correctness of our implementation and evaluation, especially if we have correctly implemented FSYNT and the baselines. We mitigate this threat by testing our implementation of all approaches on small and simple test inputs to ensure the they behave as described.

**Construct Validity:** This concerns the test oracle and failure feedback employed in our evaluation. To ensure all subjects provide the expected incomplete and (in)correct feedback, we tested the programs on sample invalid inputs and modified the subject program, if needed.

**Limited to Data Repair:** The repair produced by our approach aim to ensure maximal data recovery, but it does not ensure that the intended user information is preserved. Hence, FSYNT is limited to repair of the input data, but not the intended information.

**Input Constraints and Semantics:** FSYNT does not address concerns about recovering or preserving the input constraints or intended semantics of the input data. For instance, repairing an invalid checksum or hash requires such information, and FSYNT will be limited for this use cases. However, it would provide repair candidates that allow end-users to debug such semantic issues. In addition, inputs with significant semantic corruption may not be effectively repaired by FSYNT. Even...
though FSynth is effective in fixing structural parts of invalid inputs, when the corruption is in the semantic part, the missing data becomes difficult to recover. Examples include corrupted numbers in calculations, and dates.

**Repair via Input Synthesis:** Firstly, the repair via synthesis approach of FSynth is exhaustive, thus it can quickly become computationally expensive. Secondly, the repair via synthesis operation of our approach poses the risk of introducing input elements with unintended semantic consequences. Specifically, insertion operations may lead to data corruption and information distortion. To mitigate this threat, FSynth provides several valid candidate repairs ranked by the edit distance of each repair candidate from the original input. Hence, we encourage end-users to select the best semantically-fit repair from the potential repair candidates provided by FSynth.

**VIII. RELATED WORK**

**Black-box Input Repair:** A few techniques have been proposed to analyze input data without program analysis, albeit with the aim of understanding and localizing faults in the program. The earliest works were either focused on simplifying failure-inducing inputs \([12], [17]\) or isolating fault-revealing input fragments \([18], [19]\). Notably, the minimizing delta debugging algorithm \(\text{DDMin}\) is focused on reducing failure-inducing inputs in order to diagnose and localize faults in the program. More recently, Kirschner et al. \([6]\) proposed a maximizing variant of the delta debugging algorithm \(\text{DDMax}\) to repair invalid inputs to subsets via deletion, we compare FSynth to \(\text{DDMax}\) in this work. In contrast to \(\text{DDMax}\), FSynth also synthesizes input elements to complete input repair.

**White and Grey-box Input Repair:** Some techniques employ program analysis to fix invalid inputs. As an example, docover \([20]\) applies symbolic execution to change broken inputs to take error-free paths in the subject program. Similarly, Ammann and Knight \([21]\) proposed a method to transform invalid inputs into valid inputs by analyzing the region of the input causing the fault and changing those regions to avoid the fault. Unlike these methods, FSynth is black-box, it relies on the failure feedback of the subject program.

**Constraint-based Input Repair:** These approaches automatically learn input constraints then enforce the learned constraints to repair invalid inputs \([22], [23]\). These constraints are often extracted from valid inputs \([24], [25]\), specified with predicates \([26]\), model-based systems \([27]\), goal-directed reasoning \([28]\), dynamic symbolic execution \([22]\) or invariants \([23]\). For instance, \(S\)-DAGs \([29]\) enforce constraints on invalid inputs in a semi-automatic way. Unlike these approaches, FSynth does not learn input constraints, it employs input synthesis and failure feedback to fix invalid inputs.

**Parser-directed Input Repair:** This refers to the input repair schemes of parsers, interpreters and compilers \([8], [10], [30], [31]\). These techniques employ operations such as insertion, deletion and replacement of symbols \([32]–[34]\), extending forward or backwards from a parser error \([35], [36]\), or more general methods of recovery and diagnosis \([8], [37]\). In this work, we compare FSynth to the recovery scheme of the ANTLR parser generator \([10]\) which leverages the input grammar to guide input repair. Unlike FSynth which aims to fix an invalid input, these schemes need an input grammar, and aim to ensure the compiler does not halt while parsing.

**IX. CONCLUSION**

This paper presents FSynth, an input repair approach that employs input synthesis and lightweight failure feedback (i.e., incomplete and (in)correct checks) to repair invalid inputs. Our approach is black-box, does not require program analysis or an input grammar. We evaluate the data recovery, effectiveness, and efficiency of our approach, in comparison to the state-of-the-art methods. We show that FSynth has a very high data recovery rate, it recovered 91% of input data. It is also very effective and efficient in input repair—it completes the repair of about four in five invalid inputs (77%) within four minutes. Furthermore, we demonstrate that our approach is up to 35% more effective than the best best baseline—\(\text{syntactic} \text{DDMax}\), without using an input grammar. In summary, this work demonstrates that combining lightweight failure feedback and input synthesis are important for the effective repair of invalid inputs, especially in the absence of an input specification and program analysis.

In the future, we plan to investigate how to improve the performance of our approach by learning input semantics and constraints. We also provide our implementation, data and experimental results for easy replication, scrutiny and reuse:

https://github.com/vrthra/fsynth-artifact

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