Fuzzing with Fast Failure Feedback

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Abstract  Fuzzing—testing programs with random inputs—has become the prime technique to detect bugs and vulnerabilities in programs. To generate inputs that cover new functionality, fuzzers require execution feedback from the program—for instance, the coverage obtained by previous inputs, or the conditions that need to be resolved to cover new branches. If such execution feedback is not available, though, fuzzing can only rely on chance, which is ineffective. In this paper, we introduce a novel fuzzing technique that relies on failure feedback only—that is, information on whether an input is valid or not, and if not, where the error occurred. Our BFUZZER tool enumerates byte after byte of the input space and tests the program until it finds valid prefixes, and continues exploration from these prefixes. Since no instrumentation or execution feedback is required, BFUZZER is language agnostic and the required tests execute very quickly. We evaluate our technique on five subjects, and show that BFUZZER is effective and efficient even in comparison to its white-box counterpart.

1 Introduction

A fuzzer quickly generates artificial inputs for a program under test. A fuzzer is effective if it can explore sufficiently many regions of the input space of the program [4] and implementation [23] and is efficient if it can generate and evaluate inputs quickly [4]. Fuzzing a system requires relatively little knowledge about the program or domain, and has become one of the most popular software bug finding techniques.

The classical black-box fuzzing strategy is to generate lots of random inputs quickly, and try them one at a time against the program. While effective in quickly covering shallow code paths and identifying problems in parsing, this strategy fails when it comes to programs that require complex structured inputs. The problem is that for such programs, one needs to get past the parser by producing syntactically valid inputs to reach the semantics of the program. This is especially hard to do using a black-box approach. For example, the chance of producing a simple JSON fragment such as ‘{1}’ completely randomly is $1:256^4$ or one in four billion even when the size is restricted to just four bytes. Hence, deeper code paths and program internals of programs with complex input specifications are out of reach for traditional black-box fuzzing.

One can generate valid inputs for a program if one starts with the input grammar specification of the program, and produce syntactically conforming inputs. However, input specifications are hard to come by, and even when available, may not describe the implementation correctly — which is precisely where bugs hide. For example, even for simple formats such as JSON, there are few parsers that implement it correctly [37].

An alternative is to start with a sample set of valid inputs, and rely on mutations of these inputs for generating more inputs. The problem with this approach is that it biases the fuzzer towards inputs that are present in the neighborhood of the sample set. This reduces the effectiveness of the fuzzer. Further, generating valid inputs even with mutation of valid samples can be hard. Hence, these fuzzers commonly rely on coverage feedback from the program, with the program running under instrumentation (i.e a grey box technique). However, there can be situations in which (1) the system cannot be instrumented—for instance, because the system is written in a different programming language than what the instrumentation expects, or (2) the system code comes in read-only memory or otherwise cannot be changed, making instrumentation impossible, or (3) the system is remote, and can only be accessed through its interface. In all these situations, a black-box approach is needed.

In this paper, we propose a novel strategy for quickly generating valid inputs for black-box programs with structured inputs. Our strategy is based on two key observations. (1) Programs with complex input specifications often report failure as soon as an unexpected input symbol (a byte or a token) is present in the input. Even if the program is unable to immediately signal failure to parse or validate, they can often precisely indicate the maximal valid prefix of the input that if combined with some valid suffix will be accepted by the program. (2) Once the program can signal where a failure occurred, there are only a limited number of alternatives that can be used at that point, and it is feasible to check them all.

We use this failure feedback to generate continuations that will ultimately result in valid inputs. Our approach works on all programs that satisfy the following conditions:

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1This is the same observation made in pFuzzer from Mathis et al. [31], for white-box fuzzing, and we will be using pFuzzer as the baseline for our evaluations.
(1) The program should accurately identify and accept valid inputs and reject invalid inputs. (2) The program should distinguish between inputs that are merely incomplete (that is, there exists some suffix that will make this input valid) and those that are incorrect (such a suffix does not exist). In some cases, such as reading in a chunk of data before validating, a program may not be able to immediately identify whether an input is incomplete or incorrect. In such cases, we can also relax the second constraint to: (2) The program, when it identifies an incorrect input, should report the maximal valid prefix that was parsed by the program. That is, some actually incorrect inputs may be identified as incomplete so long as when the program, when it finally realizes that the input prefix is incorrect, precisely identifies where the failure occurred.

Neither of these conditions are onerous for parsers. Most parsers already incorporate
e these conditions as a prerequisite to help the users in fixing failures.

Given a program that can distinguish between valid, incomplete, and incorrect inputs, our strategy first produces the smallest unit input symbol accepted by the program (bits, bytes, words, or even tokens if we have further information on what is expected). This input will be typically rejected by the program as either incorrect or incomplete. If it is rejected as incorrect, the fuzzer will enumerate all possible unit symbols, and try each as a fix, one of which will be rejected by the program as merely incomplete. The fuzzer will again enumerate all possible unit symbols as a possible extension to the incomplete input. This process is repeated until either the program accepts the input or we run out of testing budget for a single item.

If on the other hand, the program is unable to distinguish incomplete and incorrect inputs immediately (without reading in further data) but provides precise feedback on where the failure occurred, we trim the input to that point, and continue generating possible continuations from that point.

In either case, we only have a fixed number of symbols to verify at each point. That is, in the first case, if we are using bytes as the alphabet, one only needs to try $|\alpha| = 256$ values at each point, requiring only $|\alpha| \times L$ executions to generate an input that is $L$ bytes long. In the second case, we only have to try a maximum of $|\alpha| \times C$ inputs at each point where $C$ is the chunk size that the program needs to read in, resulting in $|\alpha| \times \frac{L}{C} \times \sum C$ executions of the program for generating an input $L$ long when compared to $|\alpha|^L$ executions if we were reliant on traditional black-box fuzzing.

Since our approach is a black-box variation of the parser directed fuzzing used by pFuzzer, we call our prototype bFuzzer. Our approach is similar to, and was inspired by pFuzzer [31]. pFuzzer is a white-box technique, and uses dynamically tracked byte comparisons within the instrumented program to decide which next byte to append to the input. bFuzzer, instead, lets the program run uninstrumented, and simply tries all $2^8$ bytes and use any byte that lets it proceed. Why not simply use a white-box approach like pFuzzer does? Indeed, white-box approaches, where applicable, can be more effective than any black-box approach. However, the realities of software development in the real world is such that white-box techniques cannot always be applied. For example, consider cyber-physical systems such as those used by the automotive industry that are composed of multiple components. If one wants to instrument such systems, it may be necessary to instrument several components many of which may be third party with different operating systems (some of which may not even have operating systems), with severe constraints on the resources the component is allowed to consume. For example, a constraint on the memory allowed may restrict low level instrumentation. Similarly, a constraint on real-time behavior may restrict the time available for instrumentation.

While it may be possible to build specialized hardware that can allow instrumentation with limited impact, it is far easier to adapt return values to add more information about why an input is invalid (if such information is not already returned).

Interestingly, our bFuzzer approach is competitive with pFuzzer on the same subject programs from the pFuzzer paper [31]. bFuzzer obtains better coverage than pFuzzer on four out of five programs tested (INI, JSON, TINYC and MJS) while generating a much larger number of valid inputs. These inputs are also many times larger than the inputs produced by pFuzzer, which translates to larger input variety.

Our research has three key contributions:

- Our approach is the first feasible black-box approach targeting programs with complex input specifications.
- We pioneer using the program response in the form of precise information as to where the failure occurred for black-box fuzzing.
- We identify a robust method of dealing with imprecision in failure report: backtracking strategies depending on the kind of information presented, and the pattern expected.

We illustrate our approach with a detailed example in Section 2, and the algorithms involved are detailed in Section 3. We conduct an evaluation of our approach in Section 4, explain the threats to the validity of our experiments in Section 5, explore the background and competing research in Section 6, and the limitations in Section 7. Section 8 concludes.

2 Fast Failure Feedback Fuzzing in Action

Consider the following scenario: You are given a program $P$ whose behavior you want to explore. For that, you need to generate plausible inputs that quickly cover its input space, exercising all features of the input language. You are assured that it is a well behaved program with the following characteristics.

2This feature is taken advantage of by editors such as vim and emacs to precisely jump to the location of syntax error.
For the sake of exposition, let us relax our constraints on the program for a bit. Rather than assuming immediate feedback, what happens if we get the failure feedback a little later?

Continuing from before, as the program suggests, we add another random byte ‘0x23’, and program responds with ✓, we add another byte ‘0x49’. Resulting in the string ‘0xff 0xd8 0x23 0x49’. At this point, the program returns X. As before, we start replacing the last added byte with another. However, this time, none of the possible bytes could elicit any return value other than X.

Here, we do something different. We know that none of the bytes could continue the string ‘0xff 0xd8 0x23’. Hence, we go back one step, and replace ‘0x23’ with another byte, say ‘0xff’ resulting in ✓, continuing again with random bytes, we now find that ‘0xff 0xd8 0xff’ can be continued with ‘0xe0’ yielding ✓ allowing us to continue further. Note that at this point, we have already generated a valid prefix with four bytes ‘0xff 0xd8 0xff 0xe0’, confirming our guess that the mystery program is a JPEG processor. A graphical representation of the exploration of JPEG parser is given in Fig. 1.

Why backtrack? Consider this fragment below:

```python
1 data = file.read(2)
2 if data == [0xff, 0xd8]: return SOI
3 elif data == [0xff, 0xe0]: return EOF
4 elif data == [0xff, 0xd9]: return SOF0
5 elif data == [0xff, 0xe1]: return EOF
6 elif data == [0xff, 0xd0]: return SOFA
7 elif data == [0xff, 0xe2]: return EOF
8 elif data == [0xff, 0xda]: return SOS
9 elif data == [0xff, 0xe3]: return EOF
10 elif data == [0xff, 0dx]: return APP0
11 elif data == [0xff, 0xd9]: return EOI
12 else: raise Fail()
```

Here, the failure feedback is deferred. That is, we will keep receiving ✓ until both bytes have been read, at which point, the program can return X if the bytes read were not in the expected set. Hence, we need to backtrack the previous bytes where we got ✓. Since the fuzzer does not know how many bytes were read in a chunk, we start by backtracking one byte, then two bytes etc.

There is another possibility. Consider the fragment below:

```python
1 idx = file.tell()
2 data = file.read(2)
3 if data == [0xff, 0xd8]: return SOI
4 ... 5 elif data == [0xff, 0xd0]: return SOFA
6 elif data == [0xff, 0xd9]: return EOI
7 else: raise Fail(till=idx)
```

It raises the exception Fail(0) when given an input ‘0xff 0xe1’. In this case, we get an X, but with additional information — the failure occurred at the token starting at 0. However, the additional information is likely an overapproximation. In this case, the actual maximal valid prefix is ‘0xff’ even though the failure was signaled at index 0 (instead of 1). If we could trust the additional information, we would have marked ‘0xff’ at index 0 as

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3In POSIX systems, this is easily achieved through the exit-code — an 8 bit integer, and equivalents exist in other systems.
having resulted in failure, and hence, no further data will be generated starting with ‘\x00f’). Instead, when we have additional information from the program during rejection of incorrect inputs, we may assume that it is an overapproximation within a certain bound (configurable, but set to a single byte by default, which assumes no overapproximation). We then behave as if the index at which the failure was reported can have two bytes (256²) before we exhaust it.

A common case is when the format is length-delimited (as many fields in JPEG are). For example, see the below fragment from nanojpeg.py.

```python
def njDecode16(pos):
    return (nj.spos[pos]«8) | nj.spos[pos+1]

def njDecodeLength():
    if (nj.size < 2): raise Incomplete()
    nj.length = njDecode16(nj.pos)
    if (nj.length > nj.size): raise Incomplete()

The check at L5 makes the program return ✓ until the first two bytes are provided as input. These bytes are interpreted as the length of the next field (L6). Next, the program returns ✓ until there is enough data to fill the field. Here, the length field is fixed to two bytes, and any two random bytes are sufficient to populate it. Once the field is populated, the bytes in that field are interpreted as the length of the next field, and the program returns ✓ for as many bytes as specified.

This works fairly well so long as there are few such fields (filling such a field can take 2¹⁶ executions at worst if two bytes are used to specify the length), and sufficient memory is available.

A final case is when there is a lexer in front of the parser. Consider the fragment from TINYC below.

```c
pos = lexer.pos()
token = lexer.next()
if token == DO:
    statement()
token = lexer.next()
assert token == WHILE
paren_expr()
```

There are two problems here. The first is that, without additional steps, the fuzzer will only get the failure feedback at the end of completing a token, at which point, if incorrect, it may be asked to restart. When the token length is more than two bytes, it becomes expensive to generate tokens this way. One way to fix this problem is to incorporate failure feedback into the lexer. We recommend using a trie [6] that is primed with the tokens accepted by the lexer. Using a trie, we can find the precise location where token match failed, which is then returned to the user. This allows one to construct L length tokens using at most |α| × L executions rather than |α|L executions in the worst case where |α| is the number of alphabets in the input language — 256 for a byte. This leaves us with the second problem, which is that the lexer does not have the information as to what is the legal token at each point. That is, after processing the statement(), the lexer will still accept DO or IF or other tokens. Here, we use backtracking. However, rather than trying |α|L executions, we only have to try at most |α| × L × |T| executions where |T| is the number of tokens that the lexer knows about, and L is the length of the longest token.

There are a few more heuristics that we have not mentioned so far. For example, if we backtrack two bytes, and find that we still have a failure, rather than continuing the same procedure, it may pay better to shift to a dictionary based approach. We can also enhance the fuzzer with any further information given by the program, for example, the expected token at any point. We note that even when backtracking, we are always at least as good as simple random fuzzing.

3 Approach

The core of the algorithm is the generate algorithm that accepts two parameters: The validate parameter which is the external validator for the input, and prefix which is an optional prefix for the input to start from.

We begin by initializing the alphabet (L2). These are the only options we have for continuation when given a prefix. We have used CMAX set to 256 to represent all bytes as the basic alphabet. However, this can be modified by the user to either choose a restricted subset, or even completely different set of alphabets such as tokens.

Next, we do the following repeatedly until we produce a valid input: We first produce a set of choices for adding to the current prefix (L5). These are the remaining symbols from alphabet after discounting any symbols already checked. We choose one symbol, and produce a new prefix n_prefix, which is used by the validate function. The return value from validation contains information about the parse status of the newly created prefix. Based on the return value, we proceed as follows:

**Complete:** If the return value is Complete, then exploration ends (L15).

**Incomplete:** If the return is Incomplete, we are ready to add more bytes. We mark the current symbol as having been seen in this position by adding it to seen, and update the prefix to the value of new prefix (L18), update the seen values in the global list of seen values at each index for the current exploration sequence (L19), and reinitialize the alphabet. The reinitialization of alphabet is necessary in case we find a numeric failure index as we will see later.

**Incorrect:** With Incorrect, there are two possibilities. (1) When there is no number indicating the failure index, it simply means that the last symbol added was incorrect. In this case, we simply note this symbol as having been seen at this index (L24) and continue. The next iteration will replace this symbol, and will never use this symbol with this prefix again. (2) When there is a failure index, it means that the failure was signaled starting at least at that index (the index may be larger). In this case, we first check, and get the seen value from that index. Next, there is
When multiple iterations happen, it may come to a point that no symbol in the alphabet is left to be seen at a particular index. When that happens, it is an indication that we need to backtrack as we mentioned previously. The backtracking implementation is given in Fig. 4.

The final piece of the puzzle is how the program should work. Fig. 5 is a simple program ishello that checks whether the given string is hello. It demonstrates how ✓ is returned whenever the length of input (the valid prefix) is less than five bytes (L12 & L13). Similarly X is returned whenever the byte at a given index is incorrect (L3 & L8). It also demonstrates string comparison necessitating backtracking (L9 & L10). Finally ✓ is returned when the complete input matches HELLO.

Figure 5: An example program for checking if a string is hello that can be fuzzed by BFUZZER.

4 Evaluation

Our technique uses just a bit more information than random fuzzing. Hence, comparisons should ideally be with respect to pure random fuzzing. However, we do not have to actually run the fuzzers to determine how they will compare. Pure random fuzzing has only one in $|\alpha|^L$ chance of producing a string that is $L$ bytes long where $\alpha$ represents the alphabet [17]. Indeed, this is true for any fuzzer that does not or cannot rely on feedback from program, as they have to fallback on random chance to generate such strings. Since there is no other fuzzer that exploits fast failure feedback, BFUZZER is superior to other black-box fuzzers by construction.

Hence, for a more relevant and useful comparison, we use pFuzzer [31] as a baseline. Note that while pFuzzer is quite similar to BFUZZER, pFuzzer is a white-box technique while BFUZZER is a black-box technique. That is, pFuzzer operates with quite a lot more information than BFUZZER. Further, pFuzzer was shown to be better than the state of the art [31] such as AFL and KLEE [7] in generating valid inputs for programs quickly. Is this advantage preserved when we eschew instrumentation?

We use five different programs with complex input languages. These are the same programs that were used by pFuzzer for its evaluation [31], shown in Table 1. We modified each slightly so that they would provide fast failure feedback as required by BFUZZER. The number of lines added is listed in Table 1. Note that the modifications of TINYC and JSON include lines for checking whether the trie contains a given token. The implementation of trie is in a shared file (53 lines) and is not included in this count.

Table 1: Subject Programs

| Name  | Accessed   | Lines of Code | Kind | +Lines |
|-------|------------|---------------|------|--------|
| JNI   | 2018-10-25 | 293           | RG   | 5      |
| CSV   | 2018-10-25 | 297           | RG   | 1      |
| JSON  | 2018-10-25 | 2,483         | CFG  | 61     |
| TINYC | 2018-10-25 | 191           | CFG  | 60     |
| MJS   | 2018-10-25 | 10,920        | CFG  | 6      |

*Note that our claim is only applicable to programs that fulfill our criteria—availability of precise failure reports that distinguish between ✓ and X. We had to modify these programs so that they fulfill the expected criteria. If the program satisfies our criteria, we do not require the source code.
Our subjects include programs with simple regular grammars (RG) such as INI [3] and CSV [26] as well as more complex context-free grammars (CFG) such as JSON [12], TINYC [27] (a subset of the C language), and MJS [9] (a subset of JavaScript). Given that all of these languages are textual, we used the printable subset ($|\alpha| = 100$ bytes) for evaluation rather than all 256 bytes. We further set a maximum limit of 1000 bytes per input. That is, any prefix reaching more than 1000 bytes was discarded, and the computation started again. This way, we do not get stuck trying to complete deep unbalanced parentheses. The programs JSON, TINYC, and MJS use lexers with slight differences. For JSON, a lexer is used to identify true, false and null. Crucially, the lexer is used only on locations where these tokens are allowed. Hence, once the tokens are constructed, there is no backtracking required. For TINYC on the other hand, the lexer supplies the tokens to the parser, and the parser decides whether the provided token is legal or not. Hence, backtracking is required. For both, we modified the lexer to return correct feedback using a trie that was primed with the known tokens. JSON does not provide extra information on , while the TINYC always provides information on where the parse failure occurred. Since the MJS lexer was much more complex than both TINYC and JSON, we left MJS without lexer modification.

pFuzzer on the other hand, does not require a trie as it is able to recover tokens compared using strcmp and related library calls. Tries do not work well with pFuzzer as they rely on lookups rather than comparisons to determine whether the input byte is correct.\(^5\) Hence, we do not use tries for producing inputs with pFuzzer.

Each subject demonstrates a different facet of the BFUZZER algorithm. JSON demonstrates how using a trie, we can recover tokens efficiently when there are no further constraints imposed. The case of TINYC demonstrates how precise feedback can help when there are other syntactic constraints imposed on the token. The case of MJS demonstrates how backtracking can help. Finally for INI, any string is a valid prefix, and for CSV, any string is a valid input. These demonstrate how the random choice of a byte is sufficient to cover the input language effectively.

We used the implementation of pFuzzer that is available from Mathis et al. [32]. They [31] use code coverage and input coverage to evaluate pFuzzer. In particular, the input coverage is based on the number of tokens identified. Both pFuzzer and BFUZZER generate inputs with similar tokens, hence it is not a differentiating factor between the two, and it depends on chance which tokens each tool finds first.

However, there is something even more important. The essential idea of both pFuzzer and BFUZZER is to fuzz the system under test. That is, both parsers need to generate a sufficient number of inputs to exercise the underlying system. The input parser is merely a gatekeeper, and input languages such as JSON are merely containers for more interesting data. Hence, these parsers should be judged on the number and variety of valid inputs that they are able

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\(^5\)Unfortunately the tainting engine of pFuzzer crashes when including our trie implementation to the subject. Hence, we could not run pFuzzer on the subjects modified with a trie.
to produce while exercising the same inputs features. We note that coverage obtained from valid inputs is a good proxy for the parser input features exercised. Hence, we use the number of unique inputs produced, and the maximum, and mean length of inputs produced (along with structural coverage measures) as metrics to evaluate both fuzzers.

pFuzzer was run as described by the authors, and the results are provided in Table 2. Next, BFUZZER was run on the same targets, and the results are provided in Table 3. Both fuzzers were run for one hour. We monitored their coverage behavior and found that after one hour both fuzzers find new inputs only sparsely. We note that the original evaluation of pFuzzer was run for 48 hours. However, we limited our run to just one hour for two reasons: (1) Both fuzzers, if given enough time, can achieve saturation in input coverage, (2) Our aim is to show that the BFUZZER approach is a reasonable approach when one cannot instrument the program for any reason. One hour is sufficient to demonstrate this.

We evaluated both tools on a Docker container with a base system configuration of MacBookPro13,3 with a Quad-Core Intel Core i7 processor with 4 cores running at 2.7GHz. The L2-Cache was 256 KB, and L3-Cache was 8 MB. The RAM of the base system was 16 GB. The Docker container was allocated 7 cores, had 12GB RAM, and ran Ubuntu 18.04.

4.1 Discussion

Fig. 6 shows how the branch coverage evolves over time. Table 2 contains the final statistics for pFuzzer, while Table 3 contains the final statistics for BFUZZER.

We see that BFUZZER is more efficient in producing valid inputs than pFuzzer. The number of unique inputs produced by BFUZZER (Table 3) is multiple orders of magnitude larger than the inputs produced by pFuzzer (Table 2).

BFUZZER can generate unique valid inputs many orders faster than pFuzzer for all programs checked.

Similarly, BFUZZER is able to produce much larger inputs than pFuzzer (maximum length). The mean length of inputs produced by BFUZZER is also either larger, or comparable to that produced by pFuzzer, which indicates a greater variety. Finally, BFUZZER is more effective than pFuzzer for INI, JSON, TINYC, and MJS judging by the coverage obtained.

BFUZZER induced more coverage than pFuzzer for INI, JSON, TINYC, and MJS and equal coverage for CSV during a one hour run.

BFUZZER is a black-box fuzzer and hence has limited intelligence compared to pFuzzer. So why is BFUZZER more efficient than pFuzzer in producing valid inputs? And why is it more effective than pFuzzer in covering input features (except for CSV)? One reason may hark back to the primary lesson in fuzzing: When it comes to the trade off between intelligence and efficiency in generating inputs, in the absence of overwhelming advantages, efficiency usually wins [5]. Secondly, unless there is a strong rational basis for heuristics used, random methods are best at avoiding bias [21]. While the basic idea of pFuzzer (identify a failure to parse as soon as it occurs) is certainly worthwhile, we show that a simple trade off for efficiency in execution — that of randomly choosing from every option there is, in return for avoiding instrumentation overhead — has a disproportionate impact in the effectiveness.\(^6\)

However, there is an important thing to note: We do not claim that the black-box approach of BFUZZER is superior to the white-box approach of pFuzzer. The results that we see here are merely due to the constraints of the particular implementation, which is a research prototype. It is indeed possible to optimize the pFuzzer implementation such that the overhead of instrumentation is limited, and it is likely that such an implementation would be far faster than BFUZZER. Indeed, pFuzzer and its extension, IFuzzer have a lot more information to work with, which means that they can make intelligent trade offs. Hence, the evaluation is only meant to showcase the feasibility of the BFUZZER approach.

However, instrumentation hardly works in these cases:

1. The source code of the program may not be available.
2. One may not be able to modify the compiled program to insert the instrumentation.
3. The program may be using external libraries or remote interfaces for validation which are opaque to the instrumentation.
4. The particular instrumentation used by the white-box approach is unavailable in the particular language, or the particular compiler cannot be used with the program. Research prototypes are typically implemented for a single programming language, usually for a single compiler or framework such as LLVM and are using very specific library versions with their own idiosyncrasies (for example, pFuzzer instrumentation requires specific LLVM versions).
5. The program is multi-threaded, but the data structures used in the instrumentation are not thread-safe.
6. Instrumentation adds significant overhead to the program execution.
7. The particular instrumentation used affects the processing. For example, the additional overhead of instrumentation may make it impossible to observe ephemeral states (e.g. race conditions), which may influence the parsing.

Many of these conditions are often present in the real world. The main attraction of BFUZZER is that it is the only alternative so far when one has no access to instrumentation based feedback.

\(^6\)This is the same reason pFuzzer performs so well against KLEE.
There are numerous programs that process files out there\(^7\), and a significant chunk of these are handcrafted due to concerns of efficiency and ease of error reporting and recovery. However, many of these parsers are written in programming languages with limited support for instrumentation (and indeed the particular instrumentation that a white-box fuzzer may require). Hence, black-box techniques such as ours are especially important in the real world.

5 Threats to validity

Our evaluation is subject to threats to validity.

External Validity. External validity is concerned with generalizability of results. This is largely determined by how representative our data set is. In our case, the study was conducted on five programs, which are of a relatively small size. Hence, we acknowledge this threat to validity. A mitigation is that while the programs themselves are small, they are well used in the real world. JSON is the underlying data exchange format for most of the web, and its parsers are known to have inconsistencies [37]. Similarly, C underlies most modern performance sensitive code, as well as embedded systems, while JavaScript is the foundation of the dynamic web. Hence, while the programs themselves may not be representative, their input languages are representative of the real world.

Internal Validity. Internal validity is concerned with the correctness of our implementation and our evaluation. Given that our program like every other program, is subject to bugs, we acknowledge this threat to our empirical evaluation. We have tried to mitigate it by keeping our implementation as simple as possible, and ensuring that our program works well given small well understood languages with specific properties.

Construct Validity. Construct validity is concerned with whether the metric we use is actually the right metric for the property we want to measure—in our case, whether valid inputs produced and the coverage obtained are a reasonable proxy for the effectiveness of the fuzzer. Again, we acknowledge this threat to validity, and our mitigation is that both coverage and valid inputs produced are common metrics used for fuzzer effectiveness measurement.

6 Related Work

The three main approaches to fuzzing are black-box fuzzing, specification based fuzzing and white-box fuzzing [16].

6.1 Black-box Fuzzing

Black-box fuzzers operate with little knowledge of the internals or the specification of the program [4]. Given that pure random fuzzing is extremely ineffective when it comes to complex input languages, modern black-box fuzzers almost always start with a seed corpus of well formed inputs, and mutate these inputs to generate inputs that are close enough to be valid, but dissimilar enough to explore new code paths. The first fuzzer produced by Miller et al. [34] was a pure random black-box fuzzer. The advantage of black-box fuzzers is that they assume very little about the program in question, and they impose little on the program runtime (i.e. no feedback).

6.2 Specification based Fuzzing

If an input specification is available, one can instead use the specification based fuzzers such as grammar fuzzers. Such fuzzers rely on the grammar to generate well formed inputs [20]. The advantage of such fuzzers is that they are very efficient when it comes to exploring the features of the input language, and can generate valid inputs very fast. The disadvantage is that such a specification has to exist in the first place, and such specifications, when available, are often obsolete, incomplete, or incorrect. There are only a few tools such as GLADE [2] that can synthesise the input grammar from sample inputs. However, we need a corpus of sample inputs that exercise all features of the program in the first place to use them.

6.3 White-box Fuzzing

If access to program source code is available, one can rely on white-box methods such as using symbolic execution frameworks like KLEE [7] and SAGE [18] to generate inputs that explore the input space. In addition to access to the program source code, the program can also be run under instrumentation, one can make use of coverage driven fuzzers.

The white-box fuzzer pFuzzer [31] is closely related to BFUZZER, and we discuss it in detail next. Similar to pFuzzer is lFuzzer [30] which adds heuristics for extracting tokens from parsers. BuzzFuzz [15], Taint Fuzz [29] and Angora [10] also use tainting to identify the part of the input that caused the current failure, and exclusively mutate those bytes.

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\(^7\)Wikipedia lists 1,435 input formats [31].
6.4 pFuzzer

A promising approach towards generating inputs for programs with structured input is the parser directed fuzzing strategy (pFuzzer) [31]. In this approach, one starts with a random character which is fed to the program running under instrumentation. If the program rejects the input (i.e. returns a non-zero exit code), the comparisons made on the randomly chosen input character are used to substitute the compared character with one of the values it was compared to. pFuzzer uses branch coverage guidance (i.e. substitutions on inputs that covered new code are preferred) to explore all possible substitutions. Whenever the program returns with exit code zero and new branches are covered compared to the already reported valid inputs, pFuzzer reports this input as valid and marks the covered branches as covered. For example, if only digits were compared against the last character, a random digit is used to replace the last character, and the process repeats with the input that covered the most new branches until then. Proceeding in this fashion, pFuzzer generates longer and longer sequences of valid prefixes which ultimately produce valid inputs. Mathis et al. extends this approach in fFuzzer [30] which includes additional heuristics for identifying tokens which are valid at any given point. Since this includes more assumptions about the code, it is no longer comparable to BUZZER. Hence, we do not use fFuzzer as the baseline.

pFuzzer has a number of limitations that are mitigated by BUZZER.

6.4.1 Table driven parsers

Comparisons cannot be typically mined from table driven parsers, as the bytes read are not compared against but rather used to look up a table entry. We note that BUZZER does not have a problem against table driven parsers (and indeed, as a black-box fuzzer, one may not even know what kind of a program we fuzz, and hence obtaining the grammar for it may be moot).

6.4.2 Tokenization

Lexers cause a break in the data flow. That is, given this fragment,

```c
if next_char() == '(' : return LPAREN
```

LPAREN no longer has a (direct) taint (the data flow is broken), and hence is not tracked. However, BUZZER does not have a problem with this kind of code so long as there is precise failure feedback.

6.4.3 Can one trust the mined comparisons?

Comparisons may be used for either the continue parsing branch or the exit with failure branch. Consider the fragment below. Here, the byte at index c is compared to uppercase values, and if it is an uppercase value, X is returned.

```c
if input[c] in str.upper : raise Incorrect()
```

Now, consider the fragment below.

```c
if not (input[c] in str.lower) : raise Incorrect()
```

Here, we check if the byte at index c is a lowercase value, and if it is not, it returns X. Hence, there is no single pool of bytes (either compared bytes or its complement) that can be consistently used to replace the byte compared, and hence advance the parsing.

Since pFuzzer relies on compared characters as the pool from which to choose the next character, this represents a blind spot for pFuzzer. Since BUZZER does not use comparisons, this is not a problem for BUZZER.

6.4.4 Semantic restrictions

In many cases, the comparison of an input to a valid value comes after the data has been converted from string to another data type. In the below expression, the check is made to the integer value, parsed from say ‘0b11’, which results in ‘3’, and byte taints are no longer applicable to the new integer value.

```c
ival = parse_binary_digit(input[2:])
if ival != 3: raise Incorrect()
```

As in the tokenization, BUZZER does not have a problem with this if either precise failure feedback is available, or the compared value is only a few bytes long (so that it can be found by backtracking).

6.4.5 Recursion

For the basic algorithm of pFuzzer, recursion can result in degradation of performance. For example, considering a simple parenthesis language with well balanced ‘(’ and ‘)’, the probability of closing such a prefix after 100 steps is about 1%. That is, \( \frac{1}{100} \), and continues to decrease as more characters are added. pFuzzer has to rely on a number of heuristics (which are limited by definition) to avoid this.

While BUZZER suffers from the same constraint, as it is faster than pFuzzer, BUZZER is able to generate a much larger number of valid prefixes. Hence, the number of valid inputs produced is larger.

Hybrid fuzzing: Both pFuzzer and BUZZER are valid prefix based fuzzers, and can switch back and forth to each other with little effort while fuzzing the same program. This can be useful especially considering that fFuzzer which is an extension of pFuzzer has an advantage when it comes to tokens (in that it is able to identify the valid tokens at any position fast), and BUZZER has an advantage in finding continuations fast when precise feedback is available. Hence, combining them may produce a better fuzzer.

6.5 Exhaustive Testing

Bounded Exhaustive Testing [24, 25, 11] is a testing technique where the properties of a program under test are verified by exhaustively testing up to a certain depth. Exhaustive testing is a powerful technique, and Goodenough et al. [19] points out that the exhaustive technique can serve as a proof. It can also introduce oracles with higher order logic such as \( \forall, \exists \). That is, it becomes possible to say that there do not exist two floating point expressions that evaluate to the same value, or a particular grammar does not have an ambiguous parse for strings of a fixed depth, or for
all functions, a particular approximation is within bounds. Given the power of BET, it is under active research [8, 35, 13, 1]

Given the utility of BET, any approach that can reduce the cost of BET is welcome for safety critical application verification. The fast feedback fuzzing by BFUZZER can reliably prune a large part of the input quickly, and do that without running the program under instrumentation (which can incur an overhead). Hence, BFUZZER can be immediately used for BET, and can validate the properties of more programs than previously possible.

6.6 Cryptanalysis

The concept of decoding [14] where the lock is solved one tumbler or position at a time is well known in the lock picking community, and the importance of side channels are again well understood in the cryptanalysis community. Our approach is a variation of decoding number locks, and shows the deep synergy between these fields.

7 Limitations and Future Work

While our approach is better than the state of the art in quickly generating valid inputs that cover all input features in black-box settings, BFUZZER still has a number of limitations.

7.1 Dependence on immediate failure feedback

The efficiency of BFUZZER is somewhat dependent on immediate failure feedback. BFUZZER works best if the program provides immediate feedback after each byte whether the byte was expected or not. If this expectation is not met, BFUZZER can continue with a linear degradation of its effectiveness, requiring \( \frac{256L}{C} \times \sum C \) executions in comparison to just \( 256 \times L \) executions if the program provides feedback failure only after reading \( C \) bytes (on average).

However, there may be further optimizations possible. For example, if one can predict the next byte, perhaps through statistical models, especially using reinforcement learning with hidden state [36, 33, 22] one may be able to reduce the overhead even further by predicting the next byte.

7.2 Modifying the program for fast failure feedback

Given that instrumentationless fuzzing may be useful in many scenarios, and also given that our technique is actually faster than the next best technique using instrumentation, it may be worthwhile to explore how to apply BFUZZER to more programs, by getting them to provide immediate and accurate failure feedback. In combination with some static analysis, one may incorporate further information to the return values, or rearrange validation steps so that validation of earlier bytes come earlier, or splitting the comparisons similar to the AFL compare-transform pass [28] or incorporate the trie data structure to common lexer libraries for accurate failure feedback. These can likely improve the efficiency of BFUZZER, and will be a topic for future research.

7.3 Dependence on the speed of execution of the program

As with other fuzzers (similar to, but more so than pFuzzer), BFUZZER is completely reliant on the program under fuzzing being fast to execute. If the program under consideration is not speedy enough in quickly executing and returning failures, BFUZZER will not be efficient. This can be worked around to some extent by side-channels such as time to process if such information is available. For example, if we know that processing some byte takes a fixed amount of time, and taking more time can be a hint that the program input is incomplete rather than incorrect, one may use this information in combination with timeouts. Hence, this will be an area of active research for the future.

7.4 Information about the program and side channels

One may reduce the number of executions required by half if one can restrict the bytes required to only printable ASCII letters. Similarly, one may avoid combinatorial explosion during backtracking if one knows beforehand the tokens used by the program, or even a large dictionary of words likely to be used as tokens, or possible skeletal structure of the input required. Further, any side channel about how the program processes its input may be incorporated, and could make fuzzing faster and more efficient. How to do this without requiring active instrumentation will be a future focus.

7.5 Pairing with a grammar miner

We mentioned using learners to predict the next byte previously. One may also approach this in a more direct fashion. One may simply pair BFUZZER with a black-box grammar miner such as GLADE [2] and identify the input specification completely. BFUZZER would be especially complementary to GLADE as GLADE requires a few valid samples for it to learn the input specification, which BFUZZER can supply.

Further, given a grammar miner that can predict the probability of acceptance of the next byte, one may compose refute and validate hypotheses on the fly, improving the efficiency of both the fuzzer as well as the miner, achieving more than what each are capable of independently.

8 Conclusion

Traditional feedback driven fuzzers rely on running the program under instrumentation, which reduces the speed of execution of the program. However, for many real world systems, running a program under instrumentation is infeasible due to limitations in access, external libraries or language used. Hence, an efficient black-box approach is needed.

Traditional black-box techniques (and even most white-box techniques) fare poorly when it comes to programs with complex input specifications. The problem is that random generation of inputs, while good at producing unexpected inputs, are exponentially bad at producing defined values such as magic bytes and keywords, requiring \( 256^L \) attempts
to produce a keyword of length $L$. Failure feedback fuzzing is the first approach that successfully marries the wide applicability of black-box fuzzing with the effectiveness of white-box fuzzing when it comes to programs with complex input specifications.

Our approach relies on the observation that most programs provide accurate failure feedback to the user on processing a given input, which can be used to guide the fuzzer. Our BFUZeller prototype can quickly generate valid inputs that can cover all input features in an unbiased manner. While side channel attacks are a common fare in the cryptanalysis community, ours is the first work marrying side channel information to fuzzing, showing the deep synergy between the two fields.

We evaluate our fuzzer on programs that require complex inputs such as INI, CSV, JSON, TINYC, MJS, and show that our fuzzer is efficient and effective in generating valid inputs quickly, and is even more effective than pFuzzer which is a white-box technique.

Our complete implementation and experiments are available as a Jupyter notebook:

https://github.com/vrthra/bFuzzer/blob/master/BFuzzer.ipynb

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