Assisting Fuzzing with Concolic Execution

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2 Introduction and concept

An ever-present danger in today's society is memory corruption vulnerabilities in software, be they use of uninitialized memory, using dangling null-pointers, buffer overflow, memory leaks, or a fifth, sixth- or seventh vulnerabilities. An attacker could, did he know of these vulnerabilities, exploit them in order to access confidential informations, create DOS-attacks or other and as computer processing and connecting continues to be on the rise, playing a major role in present day, patching these vulnerabilities has to be a priority. This, of course, cannot be done without first discovering said bugs.

Memory corruption bugs are often-case virtually untraceable, as only specific input combinations may trigger them, or the fact that they may appear under very unusual conditions, which makes it very hard to discover, or in some cases, even reproduce them. Add thereto, the fact, that the memory corruption's effect may manifest itself far away from its source, it can also be hard to even correlate these two, once a bug has been discovered.

A variety of tools exists, with the purpose of bug-discovery, but as the bugs are often very specific, and/or wide-spread, creating a silver bullet is hard, if not impossible. Many vulnerabilities are discovered manually, however, this solution is not scalable, as software applications generally increase in size and complexity. A handful of tools exist, including fuzzers and symbolic execution engines. These do, however have, in the worst cases, deal-breaking flaws, working against them, and their usefulness.

In 2016, The Defence Advanced Research Projects Agency (DARPA) hosted the 2016 Cyber Grand Challenge, with the theme of promoting and advancing automated computer security techniques, ranging from bug-detection to bug-squashing to hacking - all without interference from the teams who've created the software. Among the programs, created for the competition was the Driller project: an extended version of American Fuzzy Lop, augmented by the concolic execution-engine, known as angr.

The idea behind this technology is to, through combining AFL with angr, mitigate as many of each of their respective drawbacks, while simultaneously utilizing both of their many advantages.

2.1 Problem statement

Does Driller display a significant difference, in terms of running time and bugs/ vulnerabilities found, when compared to "regular" fuzzing, or is the technology?

Alternatively, is Driller suffering from being too narrowly engineered, as to better fit the kind of test-binaries, given by DARPA, and so, non-usable in real day, intrusion-combating?

3 American Fuzzy Lop

This program works by feeding random input to a program, at a very high rate, some of which will hit specific vulnerabilities in said input-program. Every input fed is logged, and upon vulnerability-hit, AFL logs the input-ID. Hereafter information about where the vulnerability occurred, and which input triggered it is gatherable, based on input ID.

An advantage, as well as a drawback of most fuzzers, hereunder AFL is its execution method, which is to be as non-invasive as possible, as to prioritize speed before complexity handling. This means that AFL does not analyse a fuzzed application, but instead directly executing the application with random input, which is immensely faster than mutating qualified input variables, based on an application analysis.

3.1 Features of AFL

AFL implements a variety of features, to enhance its efficiency. In this section, I will list some of the key features, offered.

Genetic Fuzzing

When stating that the AFL fuzzing engine relies on executing applications with inputs at absolute random, one is not totally correct. This is due to the technique known as 'Genetic Fuzzing'. Genetic fuzzing means that the engine generates - *unique* - inputs at total random. Simplified, this means that the current input, that AFL is generating cannot be the same as a previously generated input. **Stable Transition Tracking**

AFL views the union of source and destination as a tuple of it's destination blocks. These tuples are prioritised, meaning that the tuples that cause the most different execution, compared to previous executions, are chosen first for future input generation. **Loop Bucketization**

For a symbolic execution engines and fuzzers alike, loops are complicated to handle, as looping potentially offers an added layer of complexity. The AFL fuzzer makes the following contortions, in order to avoid looping's added complexity, and path space requirements: When AFL detects that a triggered path contains a loop, it logs the executed loop iterations and compares this with previous inputs. The paths are grouped, based on the amount of iterations, and hereafter only *one* path in a group is selected for further fuzzing. Using this technique, $O(N)$ of the slow loop-including paths are executed, as opposed to $O(N)$ paths.

Derandomization

TODO

3.2 Limitations of AFL

Because of the union of the above techniques and its general nature, AFL is able to quickly discover a wide selection of general vulnerabilities, meaning vulnerabilities, that are triggered by some *kind* of input. When vulnerability-triggers move past general input, and into the territory of general input AFL can potentially fall seriously behind.

```c
int main(void)
{
    int x;
    read(0, &x, sizeof(x));

    if (x == 0x12345678){
        vulnerability();
    }else{
         ...
    }
}
```

Listing 1: A program that is difficult to fuzz

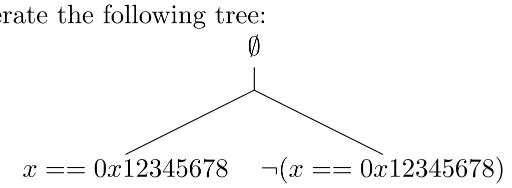
A generic example of this can be seen in Listing 1. This describes a program, that takes an input x from a user. If, and only if, x evaluates to $0x12345678$ the program will fail, as a vulnerability has been triggered, and as so, at each command, executed by the fuzzer, the frequency, and by extension, the chance of discovering the bug, is 1 in 2^{32}. Furthermore, as the AFL lacks the ability to produce new paths within this specific program lacks, it's instrumentation falls short, and AFL is reduced to randomly mutating non-instrumented input.

4 Symbolic Execution

Symbolic execution, or symbolic evaluation, is a way of program analysis, designed in order to determine the different ways said program can be executed, and which type of input causes it. Instead of executing actual values, to determine this, an interpreter assigns symbolic values to the input variables. The symbolic used to visualise how the program will execute, based on what *kind* of input it will be fed.

4.1 Features of Symbolic Execution

As symbolic execution relies on analysing input, instead of mindlessly executing input, it is able to detect specific inputs which, in this case, cause the application to crash. See Listing 1 as an example. A symbolic execution engine will analyse it's functions, and generate the following tree:



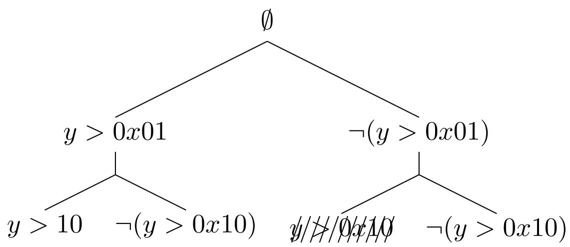
Another advantage of symbolic execution is the ability to invalidate sections input.

```c
int main(void)
{
    int y;
    read(0, &y, sizeof(y));

    if (y > 0x01){
        ...
    }else{
        ...
    }
    if (y > 0x10){
        ...
    }else{
        ...
    }
}
```

Listing 2: Example of Symbolic Execution

In Listing 2 above, for example, the input y is evaluated. A symbolic execution engine will analyse Listing 2's formulae, to find that y will either assume a value greater than $0x01$ or not greater than $0x01$. Furthermore y will either assume a value greater, or not greater than $0x10$, however greater than $0x10$ cannot occur, if y, at the same time was not greater than $0x01$. This will produce the following tree:



Because of this trait, symbolic execution's relevance to the experiment is further heightened, as this allows for AFL to exclude certain value-ranges, when mutating input.

4.2 Limitations of Symbolic Execution

Program-Dependent Efficiency

The advantage of having a symbolic execution-engine analyse paths, as opposed to input, is not present in all programs. If some inputs take the same paths in a program, the difference in analysing the inputs instead of paths, is vanishingly small.

Environment Interactions

Often programs interact with their environment, such as executing system calls and/or receiving signals. This becomes a problem when these environment factors are not under the control of the symbolic execution tool, as the tool is not able to determine branching of a program, when it has insufficient data

concerning input.
Path Explosion
The last, and possibly biggest drawback in symbolic execution engines is the path explosion problem. This problem is caused by a program that is containing loops, which causes the amount of path to grow exponentially. In theory the path amount can even become infinite, because of unbound loops. This problem is near-not-existing in small programs, however it often scales faster than the symbolically executed program scales, rendering symbolic execution virtually useless for testing medium to large applications.

5 angr: The Concolic Execution Engine

angr is a binary analysis framework, engineered modularly to be as versatile and composable as possible. Because of this, angr's use has potential to span wide, within the subject of binary analysis. Consider, for instance, just these few, but bread, uses of angr:

- angr can be used as a dynamic symbolic execution engine, which combined with value set analysis, which allows to resolve bounds on symbolic variables.
- angr can be used as a static analysis engine, which also uses concolic tracing, in order to prove that detections are not false positives.
- angr can be used as a concolic tracer, along with a fuzzer, such as AFL, in order to allow for fully automatic bug discovery, such as what was done with Driller.

Driller would receive no benefit from invoking a regular symbolic execution engine, when stuck, as AFL cannot mutate input, based on symbolic values. Instead, using angr, an execution engine with the ability to mutate concrete values, based on the values found in the previous symbolic analysis-step.

angr, based on Mayhem [2], mutates concrete values via a four steps long algorithm. The steps can be broken down into the following:

1 The input (i.e. binary code) is translated into Valgrind's VEX [3] representation in order to determine the symbolic states of the binary code.

2 Symbolic values are set in place of all non-constant variables, such as user-defined input, randomized input, environment-dependant input, etc. Constant values are represented with the same concrete values, by which they are represented in the program.

3 The values are, by execution, given constraints set up by the binary environment, as well as the concrete values described in step 2.

4 When the program reaches a new path or state, input values, which drive the program to that state is generated, based on the constraints described step 2.

At any point after the algorithm has run, the gathered concrete values can be fed to the binary code, which will trigger the binary to produce an output similar to the one, that a corresponding symbolic value has generated.

6 Driller: Concolic Execution-Assisted Fuzzing

The core assumption, when team Shellphish designed Driller, was that 99+ % of input could be divided into two categories: *general* input, spanning over a broad pallet of values and *specific* input, which is only able to take on a select few forms. Further chasing this assumption, the Driller approach emerges, which sees binaries as a collection of compartments. A representation of this can be seen in Figure 1 below:

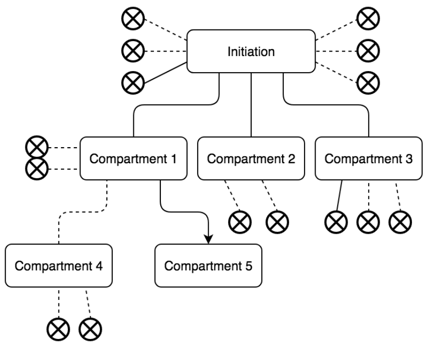


Figure 1: A graphic representation of binary compartments

In Figure 1, a path found by executing concolically is represented by a solid line, and a path found by means of fuzzing is represented by a dashed line. A bug is represented by $\otimes$.

The vast majority of bugs found in Figure 1 is found by the fuzzing component, because of its wide-spread nature. A few bugs are still discovered by the concolic execution engine, but as this technique is very slow, the task of bug-discovery is primarily left to AFL.

The task of discovering new components (i.e. paths) is primarily handled by angr. This doesn't mean that the fuzzer is unable to discover new paths, but the, sometimes very specific, input, required in order to move a program from one state to another is most efficiently handled by angr's concolic execution.

6.1 The Algorithm

Input Test Cases
Driller has no direct need for initial input test cases, and in such an instance, where non is provided, the initial fuzzing-step will work similarly to normal AFL-fuzzing. If initial test cases are provided, however, the initial fuzzing step can often times be sped up, as a tailored presence of these can guide AFL towards known compartments.
Fuzzing
When Driller is initiated, it begins by having AFL fuzz the initial compartment of the binary, which Driller has received as input. Driller discovers bugs in this compartment, by means of ordinary instrumented fuzzing, but will eventually reach a complex check, rendering AFL stuck, and therefore virtually useless.
Concolic Execution

At this point, Driller invokes its concolic execution engine angr. angr cross checks and pre-constrains the user-provided input with the input provided by AFL, in order to avoid path explosion, after which it calculates, via its constraint-solving engine, which inputs would lead execution towards a new path, towards a new compartment. If AFL has discovered, and exhausted sub-compartments before the invoking of angr's concolic execution, these already-discovered paths would represent flows of execution into new compartments.
Repeat and eventual halt
When angr is eventually done with analysing the binary, having found new execution paths, the inputs, that trigger these are passed to the "testcases" folder. When AFL's fuzzing component is again invoked, the new input will be there for future mutation. From here, AFL's state transition tracking quickly determines that the new input will result in a radically different output, which is why they are chosen first for mutation. This simple back-and-forth between angr and AFL is what, when it comes down to it, Driller is made up of, and the ping-pong repeats itself until either an input resulting in a crash is discovered, or the execution is aborted by the user.

6.2 Strengths

The advantage of the combination is great. First of all the union of these two technologies are able to mitigate each of their biggest shortcomings (i.e. path explosion and specific input), by simply passing along the task, when a problem arises. Second of all,

6.3 Weaknesses

7 Testing

7.1 Test Cases

7.2 Results

Comparable to non-instrumented Fuzzing

Comparable to Symbolic Execution

8 Conclusion

8.1 Discussion

8.2 Future Work

References

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