EffFix: Efficient and Effective Repair of Pointer Manipulating Programs

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This work introduces EffFix, a tool that applies a novel static analysis-driven Automated Program Repair (APR) technique for fixing memory errors. APR tools typically rely on a given test-suite to guide the repair process. Apart from the need to provide test oracles, this reliance is also one of the main contributors to the over-fitting problem. Static analysis based APR techniques bypass these issues only to introduce new ones, such as soundness, scalability, and generalizability. This work demonstrates how we can overcome these challenges and achieve *sound* memory bug repair *at scale* by leveraging static analysis (specifically Incorrectness Separation Logic – ISL) to guide repair. This is the first repair approach to use ISL. Our key insight is that the abstract domain used by static analysis to detect the bugs also contains key information to derive correct patches. Our proposed approach *learns* what a desirable patch is by inspecting how close a patch is to fixing the bug based on the feedback from ISL based static analysis (specifically the Pulse analyzer), and turning this information into a distribution of probabilities over context free grammars. This approach to repair is *generic* in that its learning strategy allows for finding patches without relying on the commonly used patch templates. Furthermore, to achieve efficient program repair, instead of focusing on heuristics for reducing the search space of patches, we make repair scalable by creating *classes of equivalent patches* according to the effect they have on the symbolic heap. We then conduct candidate patch validation only once per patch equivalence class. This allows EffFix to efficiently discover quality repairs even in the presence of a large pool of patch candidates. Experimental evaluation of fixing real world memory errors in medium to large scale subjects like OpenSSL, Linux Kernel, swoole, shows the efficiency and effectiveness of EffFix— in terms of automatically producing repairs from large search spaces. In particular, EffFix has a fix ratio of 66% for memory leak bugs and 83% for Null Pointer Dereferences for the considered dataset.

CCS Concepts: • **Software and its engineering → Software testing and debugging**; **Formal software verification**; *Maintaining software*; • **Security and privacy →** *Logic and verification*; • **Theory of computation → Program analysis**;

Additional Key Words and Phrases: Automated Program Repair, Incorrectness Separation Logic, Probabilistic Context Free Grammars

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1 Introduction

Despite decades of efforts put into avoiding or mitigating memory safety errors (which are errors in handling memory in native programming languages such as C), recent surveys show that this class of issues still accounts for two of the three most dangerous software weaknesses reported in 2021 [1]. For example, reports show that 60% of the high severity security vulnerabilities and millions of user-visible crashes in Android are due to incorrect memory handling, while Google announced that 70% of all security bugs in Chrome in 2020 are memory safety issues. Given the ever increasing reliance on software and its growing complexity, if left unattended, memory safety bugs in legacy code will continue to prevail and would negatively impact the user experience and trust in software. Therefore, providing the tools and technologies to fix such bugs in a timely and efficient manner is a critical endeavour. Yet, this is easier said than done.

Approaches to APR. Advances in automated program repair (APR) techniques [2] show promise in dealing with the problem of bug repair. These techniques predominantly use test cases as a specification of program correctness. However, providing only a loose specification, tests are rarely exhaustive, thus making such techniques prone to over-fitting to the test. Furthermore, the conventional generate-and-validate approach assumes the following sequence of steps for each patch candidate: select a patch from a pre-defined search space and validate it for correctness by running the patched program against the given test cases. Repeated for each candidate patch and given a sufficiently large search space, this process turns out to be quite expensive.

FootPatch [3] and SAVER [4], the state of the art techniques for repairing memory safety bugs, reduce the reliance on test suites for patch validation in favour of using the advances in static analysis to determine the correctness of patches. FootPatch demonstrates that this direction is a promising one, managing to generate fixes for large codebases. SAVER further increases the effectiveness of static-analysis based repair by designing a novel representation of the program called object flow graph which summarizes the program's heap-related behavior using static analysis, and resulting in a methodology which generates only safe fixes. However, this is still not quite enough. On the one hand, FootPatch is shown to produce unsound repairs [4], where fixing a memory leak bug could potentially lead to double-free issues. On the other hand, SAVER's reliance on its object flow graph makes it a sound tool, but it restricts its bug-fixing capabilities to only those identifiable by a specific heap access pattern. Consequently, SAVER cannot address bugs like Null Pointer Dereference, which do not conform to a specific pattern.

Our approach to APR. In this paper, we present a scalable, sound and generic methodology to fix memory related bugs without the need of test cases, implemented in a tool called EffFix. Inspired by the state of the art in repairing memory errors, EffFix relies on existing static analysis tools that are designed to find a semantically rich class of memory bugs. Differently than existing methods, EffFix is a sound and generic repair engine which is not restricted to rigid repair patterns. EffFix replaces the conventional patch synthesis followed by test-based validation with a novel synthesis and validation technique which work in tandem towards discovering what a correct patch is. In doing so it efficiently navigates the search space of candidate patches, and results in high repairability with a generic synthesis engine. To achieve this we adapt the advances of Incorrectness Separation Logic (ISL) [5, 6] for precise bug finding to the problem of automatically repairing memory leaks and Null Pointer Dereference bugs.

In a nutshell, our approach relies on ISL to describe the semantic effect the patch has on the symbolic heap, and to choose correct patches. Since the search space might be quite large, we propose to categorise patches into *equivalence classes* based on their semantic effect, and subsequently only validate one representative patch per class. Furthermore, to increase the likelihood of producing mostly correct patches, the synthesis checks how close a patch is to fixing the bug, by checking the patch's effect on the bug, and focuses on regions in the search space which have a high chance of

```
VERIFY_PARAM *VERIFY_PARAM_new(void){
    VERIFY_PARAM  *param;
    param = OPENSSL_malloc(sizeof(VERIFY_PARAM));
(+)  if (!param)
(+)          return NULL;
    memset(param, 0, sizeof(VERIFY_PARAM));
    verify_param_zero(param);
    return param;
}
```

Fig. 1. An NPD bug and its fix in OpenSSL [7].

```
static CK_RV proxy_list_slots (Proxy *py, ...) {
    ...
    slots = calloc (sizeof (CK_SLOT_ID), count);
    ...
    py->mappings = realloc (py->mappings, ...);
(+)  if (py->mappings == NULL) free(slots);
    return_val_if_fail (py->mappings != NULL,...);
   ...
}
```

Fig. 2. A memory leak bug and its fix in p11-kit [4].

producing plausible patches. In particular, we describe the entire space of solutions using a *probabilistic context free grammar* and learn which of its production rules are most likely to be involved in a plausible patch. This allows for a generic, yet efficient synthesis engine, which is not constrained by custom bug templates or specifications.

The contributions of this work are as follows:

- a *scalable* approach for static analysis driven repair; the approach partitions large search spaces into semantic effect based equivalence classes, enabling *efficient validation* and scalability;
- a *generic* APR engine based on static analysis which does not require bug specific templates or specifications to fix a given bug; instead it relies on the feedback from the analyser to understand what a bug and its correct patch are. Patch location is the only bug-specific component, and for this we provide an automatic solution to find it.
- an *effective* navigation of the solution space based on probabilistic context free grammars, which favours the production rules with higher chance of deriving a plausible patch;
- an *open source* tool, EffFix, which implements our approach to fix memory safety issues.

2 Motivation and Overview

We next highlight some of the key aspects of our approach to APR for Null Pointer Dereferences and memory leaks and support these choices by means of examples.

The case for static analysis. Consider the Null Pointer Dereference bug (NPD) in Fig. 1, a bug previously reported in OpenSSL. Under low memory, OPENSSL_malloc returns NULL, thus leading to a null pointer dereference during the call to memset which takes param as an argument. The issue here is that explicitly checking param to be a non-null value—as per the fix indicated by (+) in the considered snippet—is not a standard practice within this project since, unlike OPENSSL_malloc, most malloc wrappers in OpenSSL abort if the result is NULL. The reservations developers have in acknowledging and fixing such bugs is highlighted in the conversations the authors of a static analyser used at Meta had with the OpenSSL maintainers [5]. The memory leak in Fig. 2 happens only on a very specific program path influenced by the outcome of the call to return_val_if_fail. Attempting to resolve it on any other path could not fix the memory leak entirely, or lead to other memory safety issues. For example, if the free(slots) introduced by a naïve patch gets executed on the same execution trace as the free(slots) that already exists later in the code (for brevity, not shown in this snippet), it could lead to a use-after-free or a double-free issue.

To uncover and fix difficult to detect pointer manipulating bugs, the bug detector should understand the semantic effect a statement may have on the heap even in exceptional cases. This is hardly possible by means of dynamic testing because of the non-deterministic nature of dynamically allocated data structures and the difficulty of tracking alias information, which explains why so many memory related errors in production remain uncovered or unfixed for many years. In contrast, it has been empirically shown that static analysis is capable of uncovering even such corner cases since static analyses generally quantify over all possible effects a program may have [5]. We leverage the advances in ISL, a logic tailored for proving the presence of memory bugs, to describe the semantic effects programs have on the heap, and to guide the repair process towards the correct patch, i.e. a patch removing the unwanted semantic effects.

We shall use the potential NPD in Fig. 1 as our running example. An ISL bug detector is able to infer that a call to `OPENSSL_malloc` may result in two different valid program states, one corresponding to an empty memory footprint when the allocation fails, and another one where the allocation succeeds with a footprint comprising a single memory cell abstracted by a symbolic variable X:

$$[\mathsf{emp}]\ \texttt{param} = \texttt{OPENSSL\_malloc}(\ldots)\ [\texttt{ok} : \mathsf{param} \mapsto \mathsf{nil}]$$

$$[\mathsf{emp}]\ \texttt{param} = \texttt{OPENSSL\_malloc}(\ldots)\ [\texttt{ok} : \mathsf{param} \mapsto X * X \mapsto \_]$$

Informally, the above abstract states (simplified for brevity) read as follows: starting from an empty heap, the program may result in a valid state (indicated by the label `ok`) where the resulting pointer *points to* nil, or in a valid state where the `param` points to a symbolic heap location X that stores an unspecified value _. The first state causes issues at the call to `memset` at line 95 (ignoring the fix) since it requires `param` to point to a valid memory location. This possible Null Pointer Dereference is captured by the abstract states after the call to `memset` as follows:

$$[\mathsf{param} \mapsto \mathsf{nil}]\qquad \texttt{memset}(\mathsf{param}, \ldots)\ [\texttt{err} : \mathsf{param} \mapsto \mathsf{nil}]$$

$$[\mathsf{param} \mapsto X * X \mapsto \_]\ \texttt{memset}(\mathsf{param}, \ldots)\ [\texttt{ok} : \mathsf{param} \mapsto X * X \mapsto 0]$$

Since there is no modification in the `err`oneous symbolic state other than the label which changed from `ok` to `err`, it seems difficult to automatically derive a fix by simply looking at the program's abstract state. That is why, instead of adopting the abstract-state driven template-based patch search [3] which restricts the classes of derivable patches, we opt for a generic synthesis based on context free grammars (CFG), and only use the abstract state for validation purposes. We seek to derive patches that always lead to valid abstract states, i.e. no memory safety bugs, while keeping the code's functionality unchanged.

The case for equivalence classes. The advantages of a CFG driven synthesis are clear, i.e. genericity and simple machinery, and so are its disadvantages, i.e. poor efficiency due to a large search space which makes validation expensive. We aim to keep the advantages of our approach, while striving for efficiency. To this purpose, as we gradually derive more patches, we refine the search space of patches into equivalence classes, i.e. patches with *indistinguishable* effects on the symbolic heap, and, by doing so, we need not validate every generated patch but only one representative patch per equivalence class.

Consider the patches in Fig. 3—patches that could be generated for the example in Fig. 1. Although there are small syntactic differences between them, semantically they are equivalent. This equivalence is made obvious by the representation of the semantic effects these patches have on the symbolic heap depicted below each patch. We simplified the view of the heap, from formulae in ISL to sets of disjoint symbolic memory locations; in particular we use the empty set $\{\}$ to denote an empty memory footprint, the singleton $\{X\}$ to denote a memory footprint comprising a single memory cell, and the implication $\mathsf{param} = \mathsf{nil} \implies \texttt{ok} : \{\} \land \mathsf{ret} = \mathsf{nil}$ to denote the pair of path condition $\mathsf{param} = \mathsf{nil}$ on the left hand side of the implication, and corresponding heap abstraction on the right hand side of the implication (`ret` is a dedicated keyword indicating the returned value). In this new notation, where we no longer use ISL, the specification of the buggy program in Fig. 1 looks as follows:

$$\mathsf{param} = \mathsf{nil} \implies \texttt{err} : \{\} \land \mathsf{ret} = \mathsf{nil}$$

$$\mathsf{param} \neq \mathsf{nil} \implies \texttt{ok} : \{X\} \land \mathsf{ret} = \mathsf{param}$$

```
param = OPENSSL_malloc(...);
(+) if (!param)
(+)   return NULL;
memset(param, 0, ...);
```

$\text{param} = \text{nil} \implies \text{ok}: \{\} \wedge \text{ret} = \text{nil}$
$\text{param} \neq \text{nil} \implies \text{ok}: \{X\} \wedge \text{ret} = \text{param}$

```
param = OPENSSL_malloc(...);
(+) if (!param)
(+)   return param;
memset(param, 0, ...);
```

$\text{param} = \text{nil} \implies \text{ok}: \{\} \wedge \text{ret} = \text{param}$
$\text{param} \neq \text{nil} \implies \text{ok}: \{X\} \wedge \text{ret} = \text{param}$

```
param = OPENSSL_malloc(...);
(+) if (param == NULL)
(+)   return param;
memset(param, 0, ...);
```

$\text{param} = \text{nil} \implies \text{ok}: \{\} \wedge \text{ret} = \text{param}$
$\text{param} \neq \text{nil} \implies \text{ok}: \{X\} \wedge \text{ret} = \text{param}$

Fig. 3. Equivalent patches and their effects for the bug in Fig. 1.

```
param = OPENSSL_malloc(...);
(+) if (false)
(+)   return NULL;
memset(param, 0, ...);
```

$\text{param} = \text{nil} \implies \text{err}: \{\} \wedge \text{ret} = \text{param}$
$\text{param} \neq \text{nil} \implies \text{ok}: \{X\} \wedge \text{ret} = \text{param}$

(a)

```
param = OPENSSL_malloc(...);
(+) if (param!=NULL)
(+)   return NULL;
memset(param, 0, ...);
```

$\text{param} = \text{nil} \implies \text{err}: \{\} \wedge \text{ret} = \text{nil}$
$\text{param} \neq \text{nil} \implies \text{ok}: \{X\} \wedge \text{ret} = \text{param}$

(b)

```
param = OPENSSL_malloc(...);
(+)  param = app_malloc(...);
memset(param, 0, ...);
```

$\text{param} = \text{nil} \implies \text{ok}: \{\} \wedge \text{ret} = \text{param}$
$\text{param} \neq \text{nil} \implies \text{err}: \{X, Y\} \wedge \text{ret} = \text{param}$

(c)

Fig. 4. Non-solutions for the bug in Fig. 1.

It becomes evident that all the patches in Fig. 3 have the same effects on the symbolic heap, and we need only validate one of them to conclude the validity of all the others. The size of one such class may exponentially grow with the size of the symbolic heap and the number of existing aliases.

The case for probabilistic context free grammars (PCFG). Exploring a large search space of patches may yield significant time spent on incorrect patches. Ideally, we would like to spend less time exploring patches belonging to classes of incorrect patches, and instead focus in regions in the search space (in the form of CFG productions) which are more likely to produce correct patches. To do this we equip the CFG with probabilities which indicate the likelihood of a certain production rule to be fired in a correct patch. However, understanding what a correct patch is in the absence of a specification is tricky. We break the patch correctness criterion into three simple requirements, and show how the probabilities ascribed to the CFG change *according to how many of these requirements the generated patch respects*, or in other words, according to how *close* the patch is to fixing the bug.

To simplify our explanation, we refer to the diagram in Fig. 5: the circle labelled with (1) is the set of all possible patches, while the intersection of spaces (3) and (5) is the set of plausible patches - (3) is the set of patches that only affect the buggy path and (5) is the set of patches that fix the bug without changing the program's returned values (we informally call this *weak-functionality preservation*). (2) is the sub-space of patches which have an effect on the buggy path but do not necessarily fix the bug and, in addition, they might affect other paths too. (4) is the sub-space of patches that fix the bug, but may break functionality. Ideally, we would like to gradually bias the search spaces towards the intersection of sub-spaces (3) and (5).

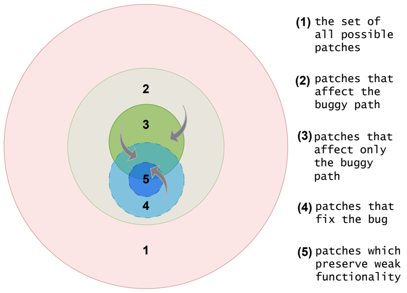

1
2
3
4
5
(1) the set of all possible patches
(2) patches that affect the buggy path
(3) patches that affect only the buggy path
(4) patches that fix the bug
(5) patches which preserve weak functionality

Fig. 5. Randomly navigate the space of patches (1) until a patch that affects the buggy path (2) is discovered. Continue the exploration in its vicinity until we hit a sub-space that only affects the buggy path (3), thus moving the exploration *closer* to discovering plausible patches. The sub-space of patches that fix the bug (4) is further refined into one with patches that preserve the code's functionality (5).

The first and most obvious requirement is for the patch to actually fix the bug. For example, all patches in Fig. 3 and the one in Fig. 4c fix the bug, however, the patches in Fig. 4a and Fig. 4b are non-solutions since they change nothing on the buggy path and therefore NULL can still flow into `memset`. We reward the production rules used in generating the patches which fix the bug (they are all in space (4) of solutions), while offering no rewards for those in the incorrect patches since they have no effect on the buggy path, i.e. patches outside space (2). An `if − then` production rule was used in generating both plausible and incorrect patches. Choosing not to reward it in the incorrect patches, instead of, say, penalizing it, allows us to still explore the space of patches containing `if − then` with the reward obtained from the correct patches, albeit guarded by different conditional expressions.

A closer inspection of the code in Fig. 4c reveals that although it fixes the NPD, this patch is actually a non-solution: apart from fixing the bug it also changes the intended functionality of the program since it affects the case where `param` is not `NULL` and introduces a potential memory leak. This leads us to *the second requirement which states that the patch should only affect the path on which the considered bug manifests*, e.g. when `param` is `NULL`, and *the third requirement which states that the patch should introduce no new bugs*; in other words, the patch in Fig. 4c is in the sub-space (4) in Fig. 5 since it fixes the bug, but not in sub-space (3) since it affects more than just the buggy path. Although a non-solution since it does not respect these two requirements, we still choose to reward the patch in Fig. 4c, albeit with a smaller reward than the patches in Fig. 3 receive. The reason for this design choice is that non-solutions may offer insights into how to remove the bug according to the sub-space they are in. For example, so far we have learnt that `if − then` is highly likely to be part of a correct patch, and that, although with a lesser probability, `app_malloc` can also fix the bug. This setup could potentially lead to a correct patch that wraps the `app_malloc` into a conditional affecting only the buggy path.

Generally, we choose to bias the search towards the space of plausible patches from two different but complementary dimensions which are evolving in parallel after a while: discovering the *correct path* and discovering the *correct effect*. To do that, the PCFG-based synthesis offers:

- no reward for the patches outside sub-space (2) since we learn nothing about a plausible fix from such patches - it is likely that at the beginning of the synthesis process most randomly generated patches will fall into this category;
- partial reward for path discovery for non-solutions in sub-space (2) but not in (3) - they offer information about the path on which we should look for a plausible patch;
- full reward for path discovery for patches in sub-space (3) - they only affect the buggy path;
- no reward for effect discovery for patches outside sub-space (4) - they do not fix the bug;
- partial reward for effect discovery for patches in (4) but not in (5) - they fix the bug but may change the program's behavior.
- full reward for effect discovery for patches in (5) - they fix the bug and preserve weak-functionality.

Sec. 3 formalises the proposed PCFG, and Sec. 5 discusses how we choose some of its parameters.

Getting back to the patch in Fig. 4c - a patch in sub-space (4) but not in (3) - we mentioned earlier that this patch receives a smaller reward than the patches in Fig. 3 receive. Yet, according to the guidelines on rewards we just mentioned it seems as if it should receive a full reward, hence seemingly contradicting our earlier statement. What happens is that the patch in Fig. 4c gets full reward for effect discovery, but gets only partial reward for path discovery, while the patches in Fig. 3 are fully rewarded for both path and effect discovery. In other words, the rewards on path and effect discovery compose leading to a smaller overall reward for the patch in Fig. 4c. This explains how non-solutions may still reveal useful information allowing the exploration of patches to get closer to plausible ones since generating solutions like those in Fig. 3 may be harder to come by as the space of plausible patches is often small, while useful non-solutions lie in larger spaces.

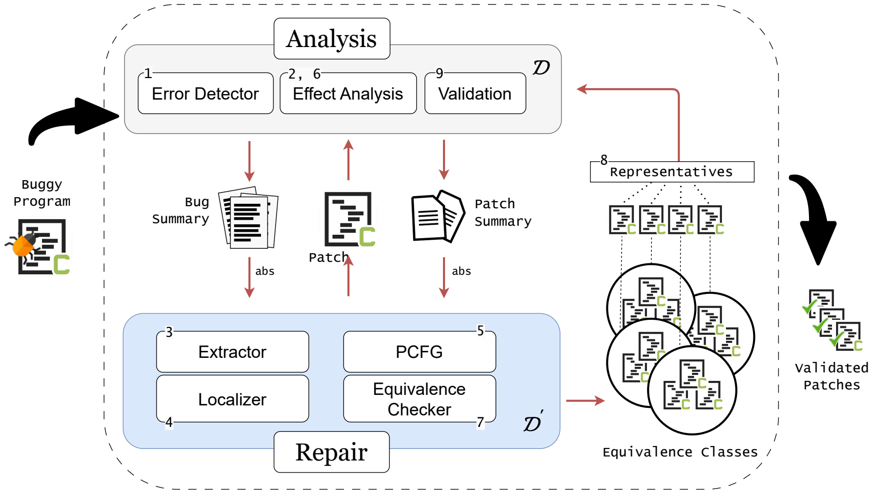


Fig. 6. Framework Overview.

SAVER [4], the state of the art in repairing memory related bugs, is unable to generate a fix for our running example since the object flow analysis on which it operates manipulates events and non-allocation cannot be modelled as an event. FootPatch does handle null pointer dereferences but its search and template-based methodology cannot always generate fixes on specific paths, if the fix template has not been seen before - leading to restrictive fixes.

3 Methodology

This section describes how bugs are detected, how patches are synthesised using probabilistic context free grammars and subsequently classified into equivalence classes according to the effect they have on the program's footprint.

3.1 Repair Framework Overview

Fig. 6 offers a summary view of our APR framework based on static analysis. In our approach, the static analysis is responsible for detecting the bug, for computing the semantic effects the bug and its corresponding patch have on the program's memory footprint, and for validating the patch. To start with, the analysis defined on an abstract domain $\mathcal{D}$ (ISL in our case) and taking a buggy program as input, detects the bug (1), computes the bug's semantic effect (2) and it then creates a summary of the bug (the footprint of the buggy method, the path condition on which the bugs manifests, and the culprit statement). The bug's summary is then used by the repair engine for extracting the ingredients for the patch (3) and for identifying the fix location (4). A patch is then synthesised using a PCFG (5). We investigate the effects the patch has on the memory footprint by creating a summary of the buggy method after having applied the newly created patch (6). Synthesised patches are then clustered into equivalence classes according to their effect on the symbolic heap (7). Only one representative patch per class (8) is then send out for validation (9). The results of the validation, e.g. does the representative patch remove the considered bug or does it affect other paths than the buggy ones, are transmitted back to the repair engine in order for it to fine-tune the probabilities ascribed to the PCFG. In other words, the probabilities implicitly reflect how the search space should be navigated. We note that, to break the dependency on the static analysis, that is, on the ISL domain, we further abstract the bug and patch summaries using a simplified abstract (meta-)domain, $\mathcal{D}'$, on which the repair functions. This meta-domain mostly retains information about what memory cells have been allocated and deallocated, and about the program paths and exit conditions.

3.2 Bug Detection

We build our approach on top of Pulse [8], an industry-grade static analysis tool which soundly detects memory safety violations. Pulse uses the latest advances in Incorrectness Separation Logic (ISL), a logic tailored to reason about the presence of bugs for heap-manipulating programs. Pulse first abstracts the C input program to an intermediate language, the Smallfoot Intermediate Language (SIL), and then runs an abstract interpretation engine to check for safety bugs.

Program model. A SIL core set of expressions and commands is depicted in Fig. 7. A program in SIL is a sequence of procedures, and a procedure is a composition of heap manipulating commands and standard commands, such as allocation, deallocation, conditionals, etc. The storage model comprises a stack and a heap, where the stack is a function from the set of program and logical variables to values, and the heap is a partial function from symbolic heap locations to values. A state thus models a stack and a heap, and together with an environment which tracks the values associated with program and logical variables it models a Pulse world.

The abstract domain ($\mathcal{D}$). The abstract domain on which Pulse operates when symbolically executing the SIL commands is depicted in Fig. 8: a symbolic heap Δ comprises a spatial term $\mathtt{k}$ and a pure, first order logical formula, π to account for pointer aliasing and non-heap information. The spatial term $\mathtt{emp}$ is an assertion to denote an empty heap, $\mathtt{v} \mapsto \mathtt{X}$ is the points-to assertion for the program variable $\mathtt{v}$, while $\mathtt{Y} \mapsto \mathtt{X}$ is the points-to for logical variables. $\mathtt{X} \not\mapsto$ denotes memory deallocation, and the separation logic conjunction $\mathtt{k} * \mathtt{k}$ denotes disjoint sub-heaps. An abstract state Φ is defined as a pair of a program path π and a symbolic heap Δ.

Bug detection. Pulse uses summaries (specifications) of predefined instructions to infer the summary (specification) of a given piece of code [5]. At the core of Pulse is the ISL (under-approximate) triple $[\Phi_{pre}]\ c\ [\epsilon : \Phi_{post}]$ which asserts that any final state satisfying Φ_{post} is reachable by executing c starting from an initial state satisfying Φ_{pre}. Furthermore, the exit condition ϵ indicates either a normal termination, i.e. $\mathtt{ok}$, or a buggy one, i.e. $\mathtt{err}$. The pair $(\Phi_{pre}, \epsilon : \Phi_{post})$ describes the effect c has on one program path, and a set F (Fig. 8) of such effects describes the memory footprint of c where each effect in the set corresponds to a unique program path.

Bug description. A bug report in Pulse comprises the information ϵ about the bug kind, e.g. null dereference, and the culprit statement c, e.g. the statement which dereferences a null pointer. On top, we record the summary of the method which contains the bug, F, and the path π, written as a first order logic formula, on which the bug manifests. A bug is defined in terms of the following tuple:

$$b ::= \langle \epsilon, \pi, c, F \rangle.$$

For a bug b we will often refer to an element of the tuple using the dot notation, e.g. $b.F$. The same notation is used throughout the paper for other kinds of tuples as well.

3.3 Patch Synthesis with Probabilistic CFGs

This section discusses the basic element of the engine for patch synthesis: the search space of all possible solutions.

CFG. Instead of working with fixed templates, we propose a synthesis engine that works over a generic CFG as the one introduced in Fig. 7 to define the search space of all possible patches. A patch P is either additive, INSERT c loc, which inserts a command c at location loc, or a deletion, COND $\mathtt{False}$ loc, which removes the command at line loc.

PCFG. We further refine the CFG in Fig. 7 into a *probabilistic context free grammars (PCFG)* tailored for our approach to APR. In a CFG, a non-terminal symbol may be expanded in n different ways, e.g. a command c in Fig. 7 may be

Variables and Values	v, x, y		Locations loc Pointers ptr ::= $v \mid \texttt{NULL}$
Boolean Expression	b	::=	$\mathsf{True} \mid \mathsf{False} \mid b \lor b \mid b \land b \mid \neg b \mid x\ op_r\ x \mid ptr\ op_p\ ptr$
Relational Operator	op_r	::=	$< \mid <= \mid == \mid != \mid > \mid >=$
Pointers Operator	op_p	::=	$== \mid !=$
Heap Manipulation	s	::=	$v := ptr \mid v := [ptr] \mid [ptr] := ptr \mid v = \mathsf{new}() \mid \mathsf{free}(v)$
Commands	c	::=	$s \mid x := f(\overline{x}) \mid c; c \mid \mathsf{ITE}(\mathsf{b}, \mathsf{c}, \mathsf{c}) \mid \mathbf{while}(b)\{c\} \mid \mathbf{return}\ x \mid \mathbf{return}\ ptr \mid \mathbf{goto}\ label$
Patch	P	::=	INSERT c loc $\mid$ COND False loc

Fig. 7. Core (Simplified) Programming Language.

Logical variables	X, Y		
Exit condition	ϵ	::=	$\{\mathsf{ok}, \mathsf{err}, \mathsf{abort}\}$
Pure term	π	::=	b
Spatial term	k	::=	$\mathsf{emp} \mid \mathsf{v} \mapsto \mathsf{X} \mid \mathsf{Y} \mapsto \mathsf{X} \mid \mathsf{X} \not\mapsto \mid \mathsf{k} * \mathsf{k}$
Symbolic heap	Δ	::=	$\mathsf{k} \land \pi$
State	Φ	::=	$\pi; \Delta \mid \exists X.\pi; \Phi$
Effect	E	::=	$(\Phi, \epsilon : \Phi)$
Footprint	F	::=	$Set(E)$

Fig. 8. Abstract domain for bug detection ($\mathcal{D}$).

Set of variables and logical variables	$Vars$		
Allocated symbolic heaps	$\mathsf{H} \subseteq Vars$		
Deallocated symbolic heaps	$\mathsf{D} \subseteq Vars$		
Aliases	$\mathsf{A} \subseteq \mathbb{P}(Vars \times Vars)$		
Meta-State	ϕ	::=	$(\pi, \mathsf{ret}, \mathsf{H}, \mathsf{D}, \mathsf{A})$
Meta-Effect	e	::=	$(\phi_{\text{pre}}, \epsilon : \phi_{\text{post}})$
Meta-Footprint	$\mathcal{F}$	::=	$Set(e)$

Fig. 9. Abstract domain for equivalence checking ($\mathcal{D}'$).

expanded in 8 different ways. In a PCFG, each production rule comes annotated with a probability p, denoting the probability of this rule being selected, with the proviso that the sum of probabilities of all n production rules should be 1, e.g. $\sum_{i=1}^{8} p_i = 1$ for the production rules of command c.

In our approach, instead of annotating the production rules with one probability, we do so with a pair of probabilities denoted by $\langle p^{\pi}, p^{e} \rangle$, with the same proviso holding separately for each probability in the pair, e.g. $\sum_{i=1}^{8} p_i^{\pi} = 1$ and $\sum_{i=1}^{8} p_i^{e} = 1$ for the production rules of command c. This design choice was made so as to be able to navigate the search space of patches from two different dimensions in parallel: finding patches with a high-probability of affecting only the path on which the bug was found (corresponding to probability p^{π}), and finding patches with a high-probability of having an effect on the heap state which fixes the considered bug (corresponding to probability p^{e}).

Assuming this pair of probabilities is set for each production rule (we detail in Sec. 3.4 how the probabilities are learnt), we generate patches by simply traversing the grammar and choosing production rules based on the product $p^{\pi} * p^{e}$, since we treat the event of generating a patch which affects the buggy path and the event of generating a patch with the correct memory effect to be independent of each other. To avoid the risk of leading to a very large (possibly infinite) parsing tree, we bound the size of the tree to a height h. However, this poses the risk of generating syntactically incorrect patches when the height h is reached. To avoid this, choosing the next production rule is a function of the rule's given probability and height: if the height of the generated tree is h, we prioritise production rules which lead to syntactically correct patches regardless of their probability; else, the probability is the sole deciding factor in choosing the next production rule.

3.4 Learning Probabilities

Starting from a PCFG with a uniform distribution (with regards to the pair of probabilities), we ascribe probabilities to this PCFG with the aim of increasing the likelihood of mostly navigating regions of plausible patches in the search space. Our strategy is to reward the production rules which lead to a patch that impacts the path the bug manifests on and those which lead to a patch that favourably affects the bug's memory footprint. This strategy allows us to learn the path the patch should affect even in the absence of a desirable effect on the memory footprint. And vice-versa.

Once a patch P has been generated from the PCFG and its effect derived, this effect is further examined to decide in which sub-space (as per Fig. 5) P belongs to and then reward the production rules which led to it accordingly. In other words, the outcome of this examination suggests how p^{π} and p^{e} of the production rules used to derive P should be adjusted, i.e. learnt. The adjustments can either be partial or full, as discussed in Section 2. For partial/full adjustment, our strategy uses pre-defined *adjustment factors* to determine how the probabilities are reassigned.

Let us assume a production rule r_1 was used in deriving P, and that the current probability of r_1 for path discovery is $p^{\pi}_1 = 0.4$. Also assume that the grammar has only three rules $c := r_1|r_2|r_3$, and that the adjustment factors for partial/full adjustments are α_p and α_f, respectively. If the examination of the effect indicates that r_1 should be given full reward for path discovery, then all probabilities for the rules in c should be adjusted. This adjustment involves re-distributing probabilities from r_2 and r_3 (the rules that were not used in deriving P) to r_1, essentially rewarding production rules that were used to derive a correct/partially correct patch. Our strategy computes the probability of *not* choosing r_1 and reassigns part of it proportional to α_p to r_1, thus implicitly de-prioritizing r_2 and r_3. Suppose $p^{\pi}_2 = 0.2$, and $p^{\pi}_3 = 0.4$. The probability of not choosing r_1 is then $0.2 + 0.4 = 0.6$. The adjustment of the probabilities for path discovery are as follows: p^{π}_1 is increased by $0.6 * \alpha_p$, while p^{π}_2 is decreased by $0.2 * \alpha_p$ and p^{π}_3 is decreased by $0.4 * \alpha_p$.

This rewarding scheme gives a higher reward when the current probability of rule being rewarded is low, and gives a lower reward when the current probability becomes higher. This design choice makes the probability learning faster initially, and smooth down later on.

3.5 Patch Clustering

To reduce the cost of patch validation we progressively refine the solution space by identifying classes of *equivalent patches*, and proceed with only validating one representative patch per class. Two patches are equivalent if we can show that they lead to patched programs which have equivalent memory footprints, or, stated differently, they have the same effect when applied on the buggy program. Given an ISL triple $[\Phi_{pre}]$ *fnc* $[\epsilon : \Phi_{post}]$, the memory footprint of *fnc* is described by the two memory snapshots/states, Φ_{pre} and $\epsilon : \Phi_{post}$, respectively. Reasoning about equivalent memory footprints would require reasoning about equivalent ISL formulas, which in turn requires ISL logic entailment checking. These requirements seem costly and highly dependent on the bug detector's domain. To break this dependency and make our approach agnostic to the bug detector, we design a meta abstraction on top of ISL which simplifies the description of the memory snapshot. Fig. 9 describes the meta domain $\mathcal{D}'$ used for equivalence checking, while, defined as a recursive function *abs*, Fig. 10 introduces some of the main abstraction rules for translating a state from ISL to $\mathcal{D}'$. A memory snapshot in $\mathcal{D}'$ is described by a tuple ϕ comprising a path π in first order logic, a return value ret described in first order logic, a set of allocated symbolic memory cells H, a set of deallocated symbolic memory cells D, and a set of pointer aliases A. A meta-effect is a tuple e which comprises the exit condition ϵ (`ok` or `err`) and two memory snapshots ϕ_{pre} and ϕ_{post}, corresponding to the inferred precondition and postcondition, respectively.

$$\frac{\Delta \vdash \mathsf{ret}}{abs(\pi; \Delta, \_) \triangleq abs(\Delta, (\pi, \mathsf{ret}, \emptyset, \emptyset, \emptyset))} \qquad \frac{}{abs(\mathsf{p}_1 = \mathsf{p}_2, (\pi, \mathsf{ret}, H, D, A)) \triangleq (\pi, \mathsf{ret}, H, D, A \cup \{(p_1, p_2)\})}$$

$$\frac{(\_, \mathsf{ret}, H', D', A') := abs(k, (\pi, \mathsf{ret}, H, D, A)) \quad (\_, \mathsf{ret}, \_, \_, A'') := abs(\pi', (\pi, \mathsf{ret}, H, D, A))}{abs(\mathsf{k} \wedge \pi', (\pi, \mathsf{ret}, H, D, A)) \triangleq (\pi, \mathsf{ret}, H', D', A' \cup A'')}$$

$$\frac{(\pi, \mathsf{ret}, H_1, D_1, A_1) := abs(k_1, (\pi, \mathsf{ret}, H, D, A)) \quad (\pi, \mathsf{ret}, H_2, D_2, A_2) := abs(k_2, (\pi, \mathsf{ret}, H, D, A))}{abs(\mathsf{k}_1 * \mathsf{k}_2, (\pi, \mathsf{ret}, H, D, A)) \triangleq (\pi, \mathsf{ret}, H_1 \cup H_2, D_1 \cup D_2, A_1 \cup A_2)}$$

$$\frac{}{abs(\mathsf{Y} \mapsto \mathsf{X}, (\pi, \mathsf{ret}, H, D, A)) \triangleq (\pi, \mathsf{ret}, H \cup \{Y\}, D, A)} \qquad \frac{}{abs(\mathsf{X} \not\mapsto, (\pi, \mathsf{ret}, H, D, A)) \triangleq (\pi, \mathsf{ret}, H, D \cup \{Y\}, A)}$$

Fig. 10. Abstract domain transformation ($\mathcal{D} \rightarrow \mathcal{D}'$).

Considering the definition of a meta domain $\mathcal{D}'$ as per Fig. 9, we can now define indistinguishable meta-effects in terms of indistinguishable states in this meta domain.

Definition 1 (Indistinguishable meta-states). Two states ϕ_1 and ϕ_2 are said to be indistinguishable, denoted by $\phi_1 \approx \phi_2$ if and only if the following condition holds:

$$\phi_1.\pi \Leftrightarrow \phi_2.\pi \wedge \phi_1.H = \phi_2.H \wedge \phi_1.D = \phi_2.D.$$

where the equality on sets is defined modulo the alias information in $\phi_1.A$ and $\phi_2.A$, respectively.

Definition 2 (Indistinguishable meta-effects). Two meta effects e_1 and e_2 are said to be indistinguishable, denoted by $e_1 \approx e_2$, if and only if the following condition holds:

$$e_1.\epsilon = e_2.\epsilon \wedge e_1.\text{pre} \approx e_2.\text{pre} \wedge e_1.\text{post} \approx e_2.\text{post}$$

So far we talked about a memory footprint as if it comprises a single pair of pre- and post-conditions. However, programs are often ascribed multiple such pairs to account for different behaviours on different program paths. A memory footprint is thus a set of pair of states in ISL, F in Fig. 8, which corresponds to a set of effect tuples in the meta-domain $\mathcal{D}'$, $\mathcal{F}$ in Fig. 9. We define indistinguishable footprints as follows:

Definition 3 (Indistinguishable meta-footprints). Two footprints $\mathcal{F}_1$ and $\mathcal{F}_2$ are said to be indistinguishable, denoted by $\mathcal{F}_1 \approx \mathcal{F}_2$, if and only if the following condition holds:

$$(\forall e_1 \in \mathcal{F}_1, \exists e_2 \in \mathcal{F}_2 : \; e_1 \approx e_2) \;\; \wedge \;\; (\forall e_2 \in \mathcal{F}_2, \exists e_1 \in \mathcal{F}_1 : \; e_1 \approx e_2).$$

In other words, two footprints are indistinguishable if they have indistinguishable meta-effects on each path. Equivalent patches are now simply defined as:

Definition 4 (Equivalent patches). Two patches P_1 and P_2 which lead to footprints F_1 and F_2, respectively, when applied to the same buggy program, are said to be equivalent if and only if their corresponding footprint meta-abstractions, $\mathcal{F}_1$ and $\mathcal{F}_2$, respectively, are indistinguishable: $\mathcal{F}_1 \approx \mathcal{F}_2$.

We use the above definition of equivalent patches to progressively partition the search space into classes of equivalent patches. The benefit of this partitioning is that we only need to validate one patch per class of plausible patches. Given a bug b, a class of plausible patches is one where all patches P meet the following condition:

$$\forall e \in P.\mathcal{F} : (e.\text{post}.\pi \Rightarrow b.\pi) \Rightarrow e.\epsilon = \mathsf{ok}$$

In other words, the path on which the bug manifests is now labelled with an ok exit condition, i.e. the bug is fixed.

3.6 Patch Location and Ingredients

Pulse reports the location where the bug manifests, but we would like a fix at its source. For this purpose we adopt and further adapt the Spectrum Based Fault Localization or SBFL [9] to static analysis settings. SBFL identifies faulty program locations by considering control-flow differences in the program executions on passing and failing test cases. These control-flow differences are then used to compute a suspiciousness score for each program element (e.g. statements or basic blocks) using various metrics such as Tarantula [10] or Ochiai [9]. SBFL requires a test suite to generate passing and failing program execution traces. We adapt SBFL to the static analysis setting where no concrete test cases are available. Our observation is that a path-based static analysis considers the program behaviors on each possible program paths, and these path-associated behaviors can be considered as "abstract tests" used in an SBFL algorithm. Concretely, based on the bug detection abstract domain described in Fig. 8, we additionally record the program statements S appeared on each path during the analysis. For each program path, we obtain the pair $\langle \epsilon, S \rangle$ where ϵ is the exit condition of the path (i.e. one of $\{\mathtt{ok}, \mathtt{err}, \mathtt{abort}\}$). The pair $\langle \epsilon, S \rangle$ can be considered as the "execution result" and the "execution trace" of an "abstract test" that drives the program through a specific path. We then compute the SBFL metric (Ochiai in our case) based on the collection of $\langle \epsilon, S \rangle$ pairs from all program paths analyzed by Pulse. We note that since Pulse already computes the exit condition ϵ for each analyzed path, our adaptation only requires minimal modification to the analysis, which is to record the statements covered during the symbolic analysis.

The SBFL result is a ranked list of statements, which serve as the candidate fix locations. We further run a simple Control Flow Graph (CFG) based CodeQL query to filter out unlikely fix locations based on the bug type. For example, for memory leaks, we only keep the descendant statements to the leak location. Users can optionally provide additional queries to refine the list of candidate locations. Finally, the filtered top-ranked locations from SBFL are used as the final set of fix locations in EffFix. We note that the patch localization is fully automated.

The patch ingredients such as variables are computed by a simple taint analysis starting from the culprit object. Other ingredients such as constants and labels are collected within the same function scope as the fix location.

3.7 Putting It All Together

Now that we have identified most phases of our approach to APR, we outline how they are interconnected in algorithm 1. Given a buggy program $\mathcal{P}$, the algorithm incrementally populates a map M with classes of plausible patches for the bugs detected by Pulse (line 4). For each bug b, it determines all the possible locations where the patch could be inserted (lines 6) and collects the ingredients for the patch synthesis (line 7). Starting from a uniform distribution of a PCFG G (line 8), the synthesis of each new patch (line 11) triggers a refinement of the patch equivalence classes and an update of the probabilities (line 12). Lastly, we validate only the classes of plausible patches (lines 13-14) by choosing a representative patch per class - we use a simple ranking metric which measures the size of the patch's AST.

Optimization. We mentioned in Sec. 3.5 that two patches are equivalent if their footprints are indistinguishable. This implies that every time we generate a new patch we should test it against every other already generated patch to check whether they are indistinguishable, or in other words whether they belong to the say equivalence class. Although correct, this would be an expensive process. Instead, we expand on the definition of indistinguishable effects to define what a summary of an equivalence class is, and subsequently only compare a newly generated patch against equivalence class summaries.

Algorithm 1: Main

```
Input: a buggy program $\mathcal{P}$
Output: a map M from bugs to sets of patches
M ⟵ InitMap()
$B$ = detect the bugs in $\mathcal{P}$
for $b \in B$ do
    locs ⟵ determine the fix location for bug $b$                    /* see Sec. 3.6 */
    $\mathcal{I}$ ⟵ collect vars and constants in $\mathcal{P}$ related to bug $b$
    G ⟵ construct a PCFG with terminals $\mathcal{I}$ and uniform distribution   /* see Sec. 3.3 */
    $C$ ⟵ $\emptyset$                                  /* empty set of patch clusters */
    for loc ∈ locs do
        while $P$ = synthesise a patch using $G, \mathcal{I}$, loc do    /* see Sec. 3.3 */
            $C$,G ⟵ RefineEquivClasses($C$,$P$,G,$b$)
    $C'$ ⟵ filter $C$ for classes of plausible patches
    $C''$ ⟵ validate $C'$ picking one patch per class
    M ⟵ update M with $b \longrightarrow$ rank($C''$)   /* rank returns the highest ranked patches */
```

Algorithm 2: RefineEquivClasses

```
1 Input: a set of existing patch clusters $C$, a patch $P$, a PCFG $G$, a bug $b$
2 Output: updated patch clusters $C$, updated PCFG $G$
3 for $cls \in C$ do
4     if $P.\mathcal{F} - b.\mathcal{F}$ == summary($cls$) then
5         $C$ ⟵ add patch $P$ to the class $cls$ of $C$
6         G ⟵ update $G$ according to $P$ and $cls$               /* see Sec. 3.4 */
7 if $P \notin C$ then
8     $C$, $cls$ ⟵ add $P$ to a new class in $C$
9     G ⟵ update $G$ according to $P$ and $cls$                   /* see Sec. 3.4 */
```

This optimizations states that two patches are equivalent if they affect the buggy program in which a bug b manifests in the same way. To this purpose, we define a *distance relation* between a patch and a bug as the symmetric set difference between the sets of allocated and deallocated symbolic heaps for each effect in P and its corresponding effect in b:

$$P.\mathcal{F} - b.\mathcal{F} \triangleq \{e_P - e_b | e_P \in P.\mathcal{F} \text{ and } e_b \in b.\mathcal{F}\}$$

where $e_P - e_b$, the difference between effects, tracks how the exit condition changed, $e_P.\epsilon \longrightarrow e_b.\epsilon$, the difference between pre-conditions, and the difference between post-conditions. $P.\mathcal{F}$ and $b.\mathcal{F}$ are the result of recursively applying the abstraction function *abs* on $P.F$ and $b.F$, respectively. The difference between meta-states is defined as follows (where r flags whether the patch changes the returned value, or in other words whether weak functionality is preserved):

$$\begin{aligned} \phi - \phi_b \triangleq \{(\pi, r, H \ominus H_b, D \ominus D_b, A \cup A_b) \quad | \quad & \pi \Rightarrow \pi_b \text{ and } r = (\text{ret} \Leftrightarrow \text{ret}_b) \\ & (\pi, \text{ret}, H, D, A) = \phi \text{ and } (\pi_b, \text{ret}_b, H_b, D_b, A_b) = \phi_b\} \end{aligned}$$

It is this difference, namely $P.\mathcal{F} - b.\mathcal{F}$, that is used as equivalence class summary. With each new patch the equivalence classes are refined as depicted in algorithm 2, where the difference between meta-states is used to determine the patch equivalence (line 4). A benefit of refining the patch equivalence using this relation is that it allows us to compute the rewards for the PCFG (according to the case analysis described at the end of Sec. 2) at the equivalence class level, instead of computing them separately for each synthesised patch (line 6 and line 9).

4 Implementation

We implemented our approach on top of Pulse[1], a sound static analyser for bug finding in the Infer toolchain used at Meta. We use Pulse to detect bugs, to derive method summaries which we then use to inspect the effect patches have on the symbolic heap, and to validate patches. We use a number of custom CodeQL queries for collecting patch ingredients. For finding fix locations we use a bespoke instance of SBFL. For checking program path subsumptions we invoke CVC4, and for quantifier elimination when dealing with logical variables in path formulas we use Z3.

4.1 PCFG Parameters

Patch size. We mentioned in Sec. 3.3 that we limit the height of a patch tree to a constant h. Initial experiments on our dataset indicated that a tree height of at most 10 allows EffFix to discover patches for most of the considered subjects. A smaller height generally yields no results since patches would be larger than that, while a larger height entails a larger timeout due to the increase of the patch search space. We found the height limit of 10 to be a good compromise between efficacy and performance, and thus imposed this limit through out the evaluation.

Adjustment factors. In the current implementation we set the adjustment factors in probability learning to be 0.1 and 0.2 for partial and full rewards, respectively. The adjustment factors are chosen such that it takes a moderate number of continuous adjustments for the learning of probability to be evident. Starting from an initial low probability for a rule (e.g. 0.1), if it takes very few adjustments to reach a high probability (e.g. 0.9), the learning process would not be gradual. On the other hand, if it takes too many adjustments, the learning process might require an extended period to take effect. With such considerations, we set the adjustment factors to be 0.1 and 0.2 in the current implementation. These values allow a probability to increase from 0.1 to 0.9 in around 10 to 20 continuous adjustments.

5 Evaluation

To empirically validate the currently proposed static analysis driven APR, we have implemented our approach in a tool called EffFix. In our empirical study, we aim to answer the following research questions:

- **RQ1 (efficacy)**: *How does EffFix perform against other similar tools?*
- **RQ2 (efficiency)**: *How efficient are the equivalence classes in reducing the validation costs?*
- **RQ3 (effectiveness)**: *How effective is the PCFG in navigating the search space of program patches?*

Dataset. We constructed our dataset of bugs to be fixed, by collecting (1) memory leak bugs from the benchmarks of SAVER [4], and (2) memory leaks and NPD bugs from OpenSSL in Pulse's benchmark [5]. In other words, we consider in our evaluation those bugs that can be detected both by the versions of Infer used by SAVER and FootPatch, and by a more recent version of Infer[2] used by EffFix. Additionally, we collected some bugs found in the Linux kernel[3] and added bugs to our dataset which were reproducible using both Infer and Pulse. SAVER and FootPatch rely on Separation Logic, a logic which over-approximates program states. This conservative approach may discover more bugs but it is prone to false positives, thus risking to put APR tools in the position of fixing non-bugs, e.g. fixing a false memory leak may lead to a double free. Instead, we built on Pulse's Incorrectness Separation Logic, which under-approximates

[1] the version which comes shipped with Infer-7499c03

[2] Infer-7499c03

[3] https://github.com/tapaswenipathak/Linux-Kernel-Infer

states, thus missing some bugs, but it guarantees EffFix only fixes true bugs. In total, there are 33 memory issues in our benchmark: 24 memory leaks and 9 NPDs. Tab. 1 contains a summary of these bugs, as well as the size of the subjects (43K - 17M lines of code) in which these bugs are witnessed.

Baseline Tools. For comparison with the state-of-the-art tools, we omit general-purpose repair tools and restrict them to special-purpose repair tools tailored for static analysis. General purpose techniques [11, 12] in theory should be able to fix all types of bugs, however, most of them are test-based techniques that rely on test cases to validate program correctness. Hence, general-purpose techniques are less effective than special-purpose techniques tailored to use static analysis output. For instance, a memory leak error cannot be fully specified using a test case. Hence, our evaluation uses two special-purpose static analysis-driven repair tools SAVER [4] and FootPatch [3] as baseline tools.

More recently, LLM-based APR techniques have been proposed for vulnerability repair [13, 14]. These techniques leverage pre-trained models which are trained using existing vulnerability-fixing commits. This could introduce data leakage in the evaluation, potentially including the fixed commits for the subjects in our evaluation data set. Furthermore, these techniques assume perfect fault localization, which requires the fix location to be provided as an input. Hence, we do not include these techniques in our evaluation.

Setup. Before conducting experiments with EffFix, we ran CodeQL and Pulse checker on each subject to generate static analysis database and bug detection reports, which serve as inputs to EffFix. Since the patch generation component in EffFix is probabilistic, we conducted all EffFix experiments with 10 repetition trials and reported the average across those 10 trials. All experiments of EffFix and comparative tools were conducted using the Cerberus framework [15].

5.1 RQ1: Comparison with Other Tools

We compare the efficacy of EffFix against SAVER [4] and FootPatch [3], the state-of-the-art static analysis driven APR tools for memory bugs. We set a timeout of 20 minutes for EffFix and SAVER, since most developers prefer APR tools to produce repairs in under 30 minutes [16]. FootPatch was given a timeout of 1 hour because no patch was produced with the 20 minute timeout.

Tab. 1 summarizes the results of comparing EffFix to SAVER and to FootPatch, respectively. The two *#Bugs* columns indicate the number of bugs found by both EffFix's underlying Pulse checker and the tool against which we compare. For example, EffFix's Pulse finds 4 memory leaks for the `openssl-1` subject, but FootPatch only finds 1 which explains why we consider 4 bugs when comparing against SAVER and only 1 bug when comparing against FootPatch for the same subject. Columns *Plausible* and *Correct* indicate the number of bugs for which each tool is able to find plausible and correct patches, respectively. A patch is plausible if it passes the analysis check, e.g. Pulse or Infer, and correct if it additionally passes manual inspection. The ground truth for the fixes in the `openssl-X` and `LinuxKernel-v5.0` subjects is provided in the form of developers' fixes, by checking the commit history of the corresponding projects. Since there is no ground truth for the benchmark of SAVER, we solely rely on manual inspection to conclude the correctness of the generated patches for the subjects pertaining to this benchmark.

Results. For memory leaks, EffFix and SAVER have similar results. Given a total of 24 considered bugs, both tools found a correct patch for 13 bugs. In other words, the tools have each a fix ratio of 54%. When comparing against FootPatch on a total of 19 memory leaks, EffFix found correct fixes for 11 bugs out of 16 bugs for which it generated plausible patches, while FootPatch found 1 correct patch out of 3 with plausible patches. That leads to a fix ratio of 57% for EffFix in this context, and of 5% for FootPatch. For Null Pointer Dereferences, EffFix finds correct patches for 6 bugs out of the 9 considered in the comparison with SAVER, and for 5 bugs out of the 6 bugs considered in relation to FootPatch. That is a fix ratio of 66% and 83% for EffFix corresponding to the two considered evaluation contexts.

Tab. 1. Comparison with static analysis based memory error repair tools in repairing C programs. Legend: kLoC: lines of code in the subject program (in thousands). #Bugs: total number of bugs being considered in the subject (we only consider bugs that can be *detected* by all tools). Plausible: number of bugs for which a tool can find plausible patches. Correct: number of bugs for which a tool can find correct patches.

Subject	kLoC	EffFix vs. Saver					EffFix vs. FootPatch				
		#Bugs	Plausible		Correct		#Bugs	Plausible		Correct	
			EffFix	Saver	EffFix	Saver		EffFix	FootPatch	EffFix	FootPatch
Memory Leaks											
Swoole (a4256e4)	43.0	3	2	2	2	2	3	2	2	2	1
p11-kit (ead7ara)	62.9	1	1	0	0	0	1	1	1	0	0
x264 (d4099dd)	73.2	6	6	6	4	3	6	6	0	4	0
Snort-2.9.13	320.8	8	6	8	4	8	8	6	0	4	0
OpenSSL-1.0.1h	279.2	4	4	0	3	0	1	1	0	1	0
LinuxKernel-v5.0	17184.7	2	2	2	0	0	0	0	0	0	0
Total		**24**	**21**	**18**	**13**	**13**	**19**	**16**	**3**	**11**	**1**
Null-Pointer Dereferences											
OpenSSL-1.0.1h	279.2	5	4	NA	3	NA	3	3	0	3	0
OpenSSL-3.0.0	480.86	3	2	NA	2	NA	3	2	0	2	0
LinuxKernel-v5.0	17184.7	1	1	NA	1	NA	0	0	0	0	0
Total		**9**	**7**	**0**	**6**	**0**	**6**	**5**	**0**	**5**	**0**

SAVER is not applicable (NA) to NPDs since it uses pre-defined fix strategies. FootPatch, although it has capabilities to fix NPDs, generated no plausible patches.

Fig. 11a captures the number of *unique* bugs each tool finds plausible patches for. EffFix found plausible patches for 11 unique bugs while SAVER found for 2 and FootPatch for 1. Fig. 11b depicts a similar diagram for correct patches, which shows EffFix finds correct patches for 10 unique bugs.

We note that although EffFix applies to NPD while SAVER does not, EffFix still correctly fixes 4 additional unique memory leaks compared to SAVER (out of the 10 unique bugs in Fig. 11b). For these 4 bugs, SAVER's custom analysis either fails to analyse the bug report, or produces a patch with wrong path condition. On the other hand, SAVER generated a correct patch for 4 bugs for which EffFix did not. EffFix failed to generate a patch due to the large (automatically) constructed search space, which could have been alleviated by using a more strict selection criteria for patch ingredients or by increasing its timeout.

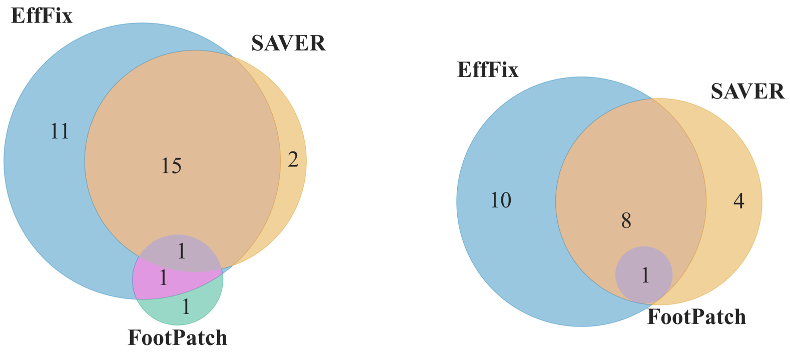
Compared to EffFix and SAVER, FootPatch found plausible/correct patches for fewer bugs. One possible reason is that FootPatch searches for candidate repair statements within the program, which could have two consequences. One is that it does not scale well for large codebases such as Snort and OpenSSL. In fact, FootPatch times out for these programs in our experiments. Another consequence is that it fails to find a patch which requires new expressions.

Time Cost. Beyond efficacy, we further examine the efficiency of the repair tools in our experiments. Tab. 2 shows the average time costs required by the repair tools for each bug where a plausible patch was successfully generated. In this context, we exclude the time spent by external tools prior to the repair experiments, including tasks like running Pulse/Infer for bug detection and building the CodeQL database. Since FootPatch combines bug detection and repair in a single run, we do not report the repair time cost of FootPatch in Tab. 2.

For EffFix and SAVER, Tab. 2 illustrates the time costs for each of their main stages. EffFix takes an average of 302.4 seconds to perform fix localization and gather patch ingredients (as discussed in Section 3.6). With the identified fix locations and ingredients, EffFix takes another 180.5 seconds to find the first plausible patch. On the other hand, SAVER

Tab. 2. Time costs of different stages in EffFix and SAVER. “Time (Patch generation)” for EffFix refers to the time taken from the start of PCFG exploration to finding the first plausible patch. “Time (Patch generation)” for SAVER refers to the time taken for constructing and relabeling its object flow graph and creating a patch.

	EffFix		SAVER	
	Time (Localization + Ingredients gathering)	Time (Patch generation)	Time (Pre-analysis)	Time (Patch generation)
Average	302.4 s	180.5 s	856.2 s	2.7 s



(a) Plausible patches

(b) Correct patches

Fig. 11. Number of bugs for which each repair tool was able to generate a plausible/correct patch. The common bugs that multiple tools can generate a plausible/correct patch for are indicated by the overlaps.

takes a longer time in its “pre-ananlysis”, 856.2 seconds on average, which is to slice the input program to reduce the cost during patch generation. During the patch generation stage, SAVER takes a shorter time of 2.7 seconds since its custom analysis is bug-specific and can be lightweight. It is possible to optimize the SAVER pre-analysis cost by running it only once per project [4]; however, since the experiments are conducted on a per-bug basis, we report the timing cost as is.

Overall, EffFix takes a comparable time to find a plausible patch as SAVER, while employing a generic technique. We note that both EffFix and SAVER take less than 20 minutes, which is within the execution time limit of automated program repair tools acceptable to developers [16].

Answer to RQ1. *For memory leaks, the results of EffFix are similar or better than the state-of-the-art in repairing such bugs. Furthermore, owning to its generic patch synthesis engine, EffFix is also effective in fixing other kind of memory safety bugs such as Null Pointer Dereferences, where the outcomes indicate better overall results than the state-of-the-art.*

5.2 RQ2: Efficiency of Patch Clustering

We evaluated EffFix’s strategy of clustering patches based on their effects. Tab. 3 details our results. We focus on the columns under *EffFix*, and postpone the discussion of those under *EffFix*$_u$ to Sec. 5.3. To counter for the randomness in the patch synthesis component, we conducted the experiments for ten trials and report the average results where appropriate. We used a 20-minute timeout for each run, which includes ingredients collection, patch synthesis and clustering. After the timeout, all patches that removed the targeted bug from the underlying Pulse analysis are considered as *plausible* (column #P$_\text{p}$). Since all patches within one cluster are equivalent in the defined abstract domain, only one representative patch per cluster is selected as candidate for (manual) validation (the patch with smallest AST size is selected as the representative). We refer to these patches as the *representative* plausible patches (column #P$_\text{rp}$).

Tab. 3. Details of EffFix (and EffFix$_u$) in fixing memory errors. Legend: #Loc: number of different fix locations considered during repair. #PI$_p$, #PI$_{np}$, and #PI$_c$: number of pointer variables, non-pointer variables and constants that are used as patch ingredients, respectively. #P$_s$: count of syntactically different synthesized patches; #C: number of equivalence classes; #P$_p$: count of plausible patches; #P$_{rp}$: count of representative plausible patches. Mean denotes the arithmetic means across bugs.

ID	**Subject**	**Type**	**#Loc**	**#PI$_p$**	**#PI$_{np}$**	**#PI$_c$**	**EffFix**				**EffFix$_u$**			
							#P$_s$	**#C**	**#P$_p$**	**#P$_{rp}$**	**#P$_s$**	**#C**	**#P$_p$**	**#P$_{rp}$**
1	p11-kit	Leak	1	7	2	3	352	90	39.2	9.7	363	100	15.2	7.5
2	Snort	Leak	1	4	3	3	214	76	0.4	0.2	297	116	0.0	0.0
3		Leak	1	4	3	3	229	59	2.5	0.6	331	77	0.2	0.2
4		Leak	2	2	5	3	165	46	0.0	0.0	300	91	0.1	0.1
5		Leak	2	3	6	3	176	78	0.0	0.0	252	106	0.2	0.2
6		Leak	2	3	7	4	185	85	0.1	0.1	241	108	0.0	0.0
7		Leak	1	6	1	2	183	84	9.3	1.1	237	130	0.0	0.0
8		Leak	1	7	1	3	231	107	5.9	0.9	236	135	0.2	0.2
9		Leak	2	3	2	3	242	68	0.2	0.2	249	89	0.0	0.0
10	Swoole	Leak	2	5	8	6	100	43	0.0	0.0	98	44	0.0	0.0
11		Leak	2	2	3	3	273	77	57.4	13.0	272	70	20.3	8.6
12		Leak	2	3	1	3	372	82	66.6	15.2	411	67	26.0	10.2
13	x264	Leak	1	3	6	3	241	38	50.0	3.7	250	40	14.5	3.2
14		Leak	1	3	4	3	1102	215	131.5	26.0	1186	180	57.0	17.6
15		Leak	1	1	1	3	498	47	85.2	9.4	605	55	38.1	8.2
16		Leak	1	3	4	3	352	156	25.7	4.9	377	168	9.8	3.1
17		Leak	1	5	5	3	323	76	34.3	8.4	333	60	11.4	5.3
18		Leak	1	6	3	5	347	97	101.0	19.8	371	108	63.5	17.6
19	OpenSSL-1.0.1h	NPD	1	1	0	3	667	39	61.8	1.3	918	38	38.8	1.5
20		NPD	-	-	-	-	-	-	-	-	-	-	-	-
21		NPD	1	1	1	4	514	22	26.7	2.0	466	28	7.8	2.0
22		NPD	1	2	0	3	744	132	130.9	4.8	1141	212	78.7	5.9
23		NPD	1	5	1	2	173	86	7.7	1.8	199	125	2.3	1.6
24		Leak	1	1	0	4	700	14	216.5	4.0	1144	16	105.2	4.0
25		Leak	2	5	4	5	216	35	15.7	5.5	225	41	11.4	5.6
26		Leak	2	9	0	4	194	48	13.9	3.6	192	49	5.6	3.9
27		Leak	2	3	0	3	140	20	16.3	5.5	153	17	5.9	3.3
28	OpenSSL-3.0.0	NPD	1	1	0	2	406	45	36.4	2.2	592	44	24.4	2.1
29		NPD	-	-	-	-	-	-	-	-	-	-	-	-
30		NPD	1	1	1	4	376	37	24.2	1.8	425	43	5.8	1.2
31	Linux-5.0.0	NPD	1	1	2	3	829	194	26.8	6.0	1073	202	11.7	2.5
32		Leak	1	6	9	2	569	78	22.4	4.8	636	66	7.8	3.4
33		Leak	2	10	5	65	449	141	39.7	15.3	485	136	16.3	12.9
Mean				3.5	2.7	5.0	350	73	**37.8**	**5.2**	426	84	**17.5**	**4.0**

Results. Column #P$_p$ and #P$_{rp}$ highlight the effect of patch clustering. On average, EffFix generated 37.8 plausible patches for each bug, and, courtesy to patch clustering only an average of 5.2 patches are selected for validation purposes. In other words, patch clustering reduced the validation efforts by about ~7x in our experiments, with the validation oracle being invoked 5.2 times on average for each bug instead of 37.8 times. The reduction in validation costs benefits not only the automated validation oracles such as static analyzers, but also the human developers who examine the plausible patches.

To give a complete picture to the reader, we discuss the bugs that could not be handled by EffFix. We note that EffFix did not generate plausible patches for 3 bugs (Bug 4, 5 and 10) in all trials. The main reason for not finding plausible patches within the timeout is likely the large search space. This larger search space is due to the relatively higher numbers of fix locations and other patch ingredients. Besides, EffFix did not work for Bug 20 because its bug trace spans multiple functions, which is not supported by our prototype implementation. Furthermore, EffFix also did not produce reliable results on Bug 29 because the program's abstract state hits the limit of disjuncts allowed by Pulse once the patches were applied to fix the buggy code. What this means is that although Pulse detects the bug in the original code,

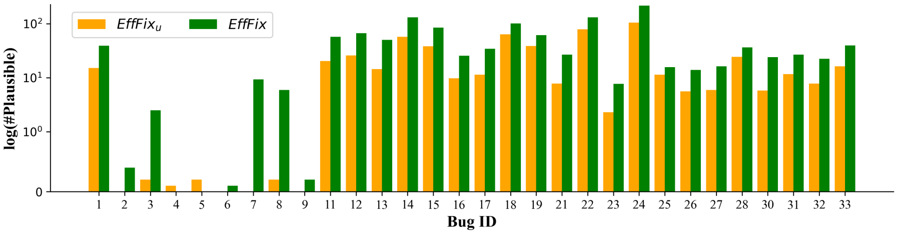


Fig. 12. Average number of plausible patches generated by EffFix and EffFix$_u$ for each bug, across 10 trials. Numbers are plotted in symmetric log scale. Bugs for which both tools found no plausible patches are excluded.

it is not guaranteed that it can still prove its presence after applying a possible incorrect patch if the patch increased the number of disjuncts above the limit which guarantees the soundness of the tool. Nevertheless, for other bugs which EffFix can find plausible patches for, patch clustering significantly reduces the validation effort. For example, for several bugs (e.g Bug 13, 19, 24, etc.), more than 90% of the plausible patches were identified as equivalent to the others, which means they can be excluded in future validation processes.

Answer to RQ2. *Partitioning large search spaces into semantic effect based equivalence classes increases the efficiency of patch validation by up to 7x even for large scale codebases.*

5.3 RQ3: Effectiveness of Probabilistic Grammar

We next investigate the effects of using a PCFG to navigate the search space. We performed an ablation study by disabling the probability learning in the PCFG. In other words, the same PCFG with a uniform probability distribution is used for both the patch synthesis and the clustering process. We refer to this version of our tool as EffFix$_u$ (with uniform probability distribution).

Results. The results of evaluating EffFix$_u$ are shown in Tab. 3, under the columns for *EffFix$_u$*. Overall, the results show that EffFix$_u$ finds lesser plausible patches on average, compared to EffFix (17.5 vs 37.8). The difference in numbers of plausible patches for individual bugs is also captured in Fig. 12, which shows the numbers of plausible patches for each bug in log scale. Fig. 12 shows that, for the bugs in the benchmark, EffFix consistently generated more plausible patches than EffFix$_u$. This difference is likely due to the search bias: if the search is gradually guided towards regions of plausible patches by updating the PCFG, more plausible patches would be synthesized within the same time budget. Finding more plausible patches can also lead to more correct patches to be found. This is evident for the `Snort` subject, where EffFix$_u$ finds few or no plausible patches (for Bugs 2-9), and correct patches for 0/8 bugs. On the other hand, EffFix explores significantly more plausible patches, and finds correct patches for 4/8 bugs (as reflected in Tab. 1).

Furthermore, apart from exploring more plausible patches, EffFix also explores a higher number of plausible *regions*. On average, EffFix finds 5.2 plausible clusters while EffFix$_u$ finds 4. Nonetheless, EffFix$_u$ synthesized more patches on average (426 vs. 350) and created more clusters (84 vs. 73). This indicates that, although EffFix$_u$ explores more different regions in the search space, it explores more *implausible* regions compared to EffFix. EffFix, although synthesized less patches and explored fewer regions, was able to spend the time budget focusing on a larger number of plausible regions.

Answer to RQ3. *Augmenting the CFG with probabilities makes the navigation of the solution space more effective, guiding the search towards spaces more likely to contain plausible patches.*

Tab. 4. Effect of adjustment factors in EffFix. α_p and α_f are the adjustment factors for partial and full rewards, respectively.

		$\alpha_p = 0.025, \alpha_f = 0.05$	$\alpha_p = 0.1, \alpha_f = 0.2$	$\alpha_p = 0.25, \alpha_f = 0.5$
# Equivalence classes	Mean	128	114	91
	Median	119	106	79
# Plausible patches	Mean	59	58	43
	Median	20	30	27

Tab. 5. Effect of maximum patch tree height in EffFix.

		height = 5	height = 10	height = 20
# Equivalence classes	Mean	88	99	119
	Median	71	90	112
# Plausible patches	Mean	41	60	61
	Median	30	37	35

5.4 Effects of Parameters

We further conducted another set of experiments to study the effect of different parameter values in EffFix. Specifically, we alter the values of adjustment factors and patch tree height limit and run EffFix on our benchmark subjects again. Under different parameter values, we examine how these parameters affect the number of equivalence classes and plausible patches found on average.

Tab. 4 shows the results from different adjustment factors α_p and α_f. Adjustment factors control the rate of probability learning in the PCFG. With a set of large adjustment factors (e.g., $\alpha_p = 0.25, \alpha_f = 0.5$), certain production rules in the PCFG may reach a very high probability (e.g., > 0.9) after a few rewards, which will make other production rules very unlikely to be used. This may result in a less diverse set of patches being discovered. As shown in Tab. 4, large adjustment factors resulted in a lower number of equivalence classes and plausible patches being found. On the other hand, smaller adjustment factors (e.g., $\alpha_p = 0.025, \alpha_f = 0.05$) permits the usage of various production rules and can result in a more diverse set of patches: with this setting, EffFix discovered more equivalence classes of patches. However, although boosting patch diversity, smaller adjustment factors may fall short in generating more plausible patches from the few favorable classes. For example, $\alpha_p = 0.025, \alpha_f = 0.05$ resulted in a lower median number of plausible patches. The default adjustment factors used in the evaluation of EffFix (i.e., $\alpha_p = 0.1, \alpha_f = 0.2$) set a moderate rate of probability learning, striking a balance between generating more plausible patches and exploring different equivalence classes.

Tab. 5 shows the result from altering the maximum patch tree height limit. A small height limit (e.g. height = 5) only allows patches with smaller syntactic size to be generated from the grammar, thus limiting the kinds of patches explored. As a result, a small height limit resulted in both lower numbers of equivalence classes and plausible patches, as shown in Tab. 5. Increasing the height limit from 10 to 20 resulted in more equivalence classes of patches, but did not significantly increase the number of plausible patches (e.g. 61 vs. 60). This result suggests that although a larger height limit can result in more diverse patches, having a height limit of 10 equal to the one we used to evaluate EffFix is sufficient in the context of fixing memory safety errors.

5.5 Case Study

We conduct a case study on a memory leak bug in the x264 library. x264 is a library and application for encoding video streams into a specific compression format. The relevant buggy code snippet, together with the patches generated by EffFix and SAVER for this bug, are shown in Fig. 13. FootPatch did not generate a patch for this bug within our experimental timeout. This bug was detected by Pulse, and the bug manifests because of the buffer allocation on Line 3

```
1  static int open_file( char *psz_filename, hnd_t *p_handle, video_info_t *info, cli_input_opt_t *opt ) {
2      // ... other code ...
3      avs_hnd_t *h = calloc( 1, sizeof(avs_hnd_t) );
4      if( !h ) {
5          return -1;
6      }
7      __return_val = custom_avs_load_library( h );
8      // EffFix patch: + if (h == h && __return_val != 0) { free(h); }
9      // SAVER patch:  + if (true) { free(h); }
10     FAIL_IF_ERROR( __return_val, "failed to load avisynth\n" );
11     h->env = h->func.avs_create_script_environment( AVS_INTERFACE_25 );
12     // ... other code ...
13 }
14 // x264cli.h
15 #define RETURN_IF_ERR( cond, name, ret, ... )\
16 do\
17 {\
18     if( cond )\
19     {\
20         x264_cli_log( name, X264_LOG_ERROR, __VA_ARGS__ );\
21         return ret;\
22     }\
23 } while( 0 )
24 #define FAIL_IF_ERR( cond, name, ... ) RETURN_IF_ERR( cond, name, -1, __VA_ARGS__ )
25 // input/avs.c
26 #define FAIL_IF_ERROR( cond, ... ) FAIL_IF_ERR( cond, "avs", __VA_ARGS__ )
```

Fig. 13. A memory leak in x264 and the patches from EffFix and SAVER.

to the pointer h which was not freed on the path ending at Line 10. Thus, when __return_val[4] evaluates to a non-zero value in the condition, the function exits with a leaked memory buffer.

To fix the bug, a correct patch should free the leaked memory buffer on the erroneous path (i.e. the path in which FAIL_IF_ERROR returns from the function). However, it would be difficult to precisely identify the correct path on which the buffer should be freed, since FAIL_IF_ERROR is defined as a macro. Line 14-26 in Fig. 13 shows the actual macro definitions, where the actual if statement is hidden inside nested macro definitions (FAIL_IF_ERROR -> FAIL_IF_ERR -> RETURN_IF_ERR), and these macros are even defined in different source code files. For this bug, SAVER generated the patch on Line 9, which frees the buffer h with the wrong path condition (true). This patch removes the memory leak, but introduces a new memory safety issue. If the function does not return at Line 10, the variable h will be used in the rest of the function (e.g. on Line 11), resulting in a use-after-free since h has been freed in all subsequent paths. Since SAVER performs its own custom analysis to compute the path conditions, the analysis may miss certain conditions, resulting in a patch that manipulates the memory on a wrong path. In contrast, EffFix analyzes the semantic effect of a patch on top of the abstract domain used by existing analyzers for bug detection. Since ISL accurately captures the erroneous path condition (even though it is defined in nested macros), EffFix utilizes this information to identify the semantic effect that leads to a safe patch. In this case, EffFix synthesized the patch shown on Line 8, and this patch correctly fixes the memory leak without introducing new bugs.

5.6 Discussion

Extension to Other Kinds of Bugs and Languages. EffFix is driven by static analysis, meaning its effectiveness is directly tied to the quality of the analysis tool, that of Pulse in this case. We showcased how repair can be achieved for the two kinds of bugs Pulse was designed to work for, namely memory leaks and Null Pointer Dereferences. If the analysis would be able to soundly discover other kinds of bugs, e.g. buffer overflows, then we conjecture that EffFix could work with those bugs too, since its CFG for patch generation is generic enough to account for the repair of other

[4] The program was instrumented beforehand to store the return values of the function calls into variables so that the repair tools can use them.

memory safety issues, e.g. insert appropriate symbolic bounds check to avoid buffer overflows or overruns. Furthermore, we have only experimented with C programs, which is what Pulse was designed to work best for. Adapting EffFix to generate patches for a new language would simply involve tailoring the CFG to align with the specific features of the target language. The operations at the meta domain level would remain unchanged, meaning that no additional modifications would be necessary for EffFix to work with the new language. However, the bottleneck lies in having a static analysis tool that (1) soundly identifies these bugs and (2) can symbolically represent the method's footprint, similar to how ISL does, therefore enabling the derivation of equivalence classes based on the symbolic effects of the patches on the method's footprint.

Soundness of Equivalence Classes. The translation from the analysis abstract domain $\mathcal{D}$ to the meta-domain of the patch equivalence check $\mathcal{D}'$ is an overapproximation, so it could potentially cluster together patches that are not strictly equivalent if we consider the functionality changes. In other words, with regards to their semantic heap effect, a class of equivalent patches contains only equivalent patches. The information contained by an abstract state in the meta-domain $\mathcal{D}'$ is equivalent to the corresponding abstract state in the ISL domain $\mathcal{D}$, with the exception of the non-aliasing information implicitly contained by the separating conjunction. This additional information is crucial for the soundness of the analysis where abstract states are discovered as the analysis for bug detection advances. However, for the purpose of checking equivalence classes this information is not crucial since the abstract state is already soundly computed by ISL—the aliasing information captured by the alias set A in the meta-state suffices. In that sense, $\mathcal{D}'$ is an overapproximation of $\mathcal{D}$, so two originally equivalent classes in $\mathcal{D}$ can never become not equivalent in $\mathcal{D}'$. However, theoretically, due to the overapproximation some originally not equivalent patches in $\mathcal{D}$ could become equivalent in $\mathcal{D}'$. This overapproximation could lead to EffFix missing some correct patches.

Limitations. A human oracle currently checks for plausible but incorrect patches which break functionality beyond changes in the heap's shape. To ensure that we do not fix false positive bugs, we chose to build on top of Pulse since it has been shown to be sound with regards to bug finding, although incomplete. This takes care of the false positives concern specific to static analysis.

Threats to Validity. The benchmarks we chose for evaluation might not be representative for the classes of bugs we tackle, but we are constrained by the bugs discovered by both Pulse via EffFix, and by Infer via SAVER and FootPatch—the state-of-the-art in fixing memory errors for C/C++ programs. Furthermore, these APR tools are built for different categories of bugs, e.g. SAVER cannot handle NPD but fixes use-after-free/double-free, while FootPatch targets resource leaks too. Lastly, EffFix relies on the availability of the full source code involved in a memory safety issue. To mitigate this restriction, we modelled in Pulse the library calls whose source code is unavailable - we instructed Pulse with models for operations on `string`, such as `strlen, strdup, strcpy`, etc.

6 Related Work

Automated Program Repair. Many program repair techniques have been studied in the last decade, largely to fix logical errors. Recently the research community has studied fixing security vulnerabilities [17, 18], race conditions [19], students' programming assignments [20], and so on. Program repair techniques can be classified into semantic repair [12, 21], search-based repair [11, 22, 23], or learning-based repair [24, 25]. Search-based repair techniques are known as generate-and-validate techniques, which heuristically search for a candidate patch in the space of program edits and validate to find a correct patch. Generally, validation is done using dynamic analysis with the aid of a test suite. EffFix uses static analysis to validate the generated patches. Using logic-based semantic reasoning, EffFix provides additional evidence of correctness for the generated patches, thereby avoiding the patch over-fitting problem [26, 27] as well.

Fixing memory errors has been studied previously using dynamic analysis [17, 18, 28, 29], static analysis [3, 4, 30–32] and combination of both [33]. Dynamic approaches require a running test case as a witness for the memory error and are effective in fixing buffer-overflows [17, 18], NPD errors [28, 32, 34]. NPEX [32] and CONCH [34] are both specialized techniques focused on fixing Null Pointer Dereference issues. NPEX [32] uses symbolic execution to infer a program specification and a learning model to generate patches. The inferred specification is reused to verify the correctness of the generated patch. CONCH [34] constructs the inter-procedural control flow graph to extract the context, identify the fix location, and validate the generated patch. In both techniques, the repair capability is tailored to fixing null pointers only, whereas EffFix can be extended to other kinds of bugs too by extending its CFG, e.g. memory leaks.

Our work is closely related to the static analysis-based repair of memory errors [3, 4]. FootPatch [3] generates patches for heap property violations detected using Infer [35]. Similarly, SAVER [4] generates safe patches for memory errors detected by Infer [35] and was shown to be scalable for larger programs. In both techniques, the patch generated is directly tied to the class of error reported by the static analyser. In contrast, EffFix uses a generalized grammar to synthesize patches of arbitrary types. Using a probabilistic grammar EffFix can dynamically adjust the probabilities to guide the search to correctly identify repair patterns, i.e. towards a suitable path condition or memory effect, which leads to finding more plausible patches. Developed at the same time with EffFix, ProveNFix is a static analysis tool grounded in temporal logic to detect violations of temporal properties at scale [36]. The authors show how memory bugs can be formalized as violations of temporal properties, and enhance ProveNFix with repair capabilities to fix them. However, their approach is not directly comparable to ours since it is not fully automated thus adding annotation burden on users who have to describe the bugs as violations of temporal properties and annotate the project accordingly.

Another line of work for APR is using advances in machine learning to train models capable of repairing various classes of software vulnerabilities. VRepair [13] is a recently proposed approach that employs an encoder-decoder transformer, with transfer learning from bug fixing commits to fix vulnerabilities in C/C++ programs. VulRepair [14] utilizes a pre-trained Code-T5 model with BPE tokenization to handle out-of-vocabulary problems. VulMaster [37] proposed a FiD architecture to extend the context limitation in Large Language Models (LLMs), and combines it with an effective method to incorporate a diverse set of information on the vulnerability. EffFix differs from this line of works which requires training on a large data corpus and requires the user to provide a fix location. EffFix can automatically determine the fix location for an identified vulnerability type and efficiently explore the search space of program edits to find the correct patch.

More recently, InferFix [38] was proposed to use a combination of a fine-tuned LLM for program repair and static analysis bug reports to detect and fix NPDs, resource leaks, and thread safety violation bugs in C# and Java projects. While we are optimistic about the future of APR leveraging generative AI, we believe our work is complementary and supports the continued advancements of non-AI approaches since a combination of the two is more likely to yield superior results in the future [39].

Equivalence Classes. Equivalence relations have been shown to benefit many search problems involving large search spaces such as mutation testing [40–42] and compiler testing [43, 44]. Recently, it was demonstrated to be effective for APR as well [45]. Equivalence relations can be used to explore larger patch spaces more efficiently. Value based test-equivalence used in [45], partitions the patch space based on runtime values observed during test executions. In contrast, EffFix defines an equivalence relation based on effect analysis.

Probabilistic Grammar. Augmenting probabilities with grammar production rules has been shown to be useful in program synthesis [46–48] and software fuzzing [49, 50]. Using a probabilistic grammar a software fuzzer can generate inputs based on production rule prioritization. In particular, previous work [50] has shown that evolving a probabilistic grammar can direct the search towards interesting inputs by favouring specific production rules. In contrast, EffFix uses a probabilistic grammar to generate program edits rather than program inputs. It evolves the probabilities to find a plausible patch by prioritizing the most promising production rules.

7 Concluding Remarks

This work introduced an automated program repair approach guided by static analysis. Our repair technique fixes null pointer dereferences and memory leaks. In our workflow, static analysis is used to both discover and fix a bug, thus alleviating the classic over-fitting issue that test-based approaches normally suffer from. The novelty of our approach is two-fold. First, modulo the patch location, it is generic, requiring neither patch templates nor bug specifications. Instead, the repair engine incrementally *learns* what a correct patch may look like based on its effect on the symbolic heap. It stores this knowledge as a distribution of probabilities over a context-free grammar. Furthermore, we have empirically shown that the use of probabilistic context-free grammars leads to an effective patch space navigation. Second, to cope with the large search space of candidate patches, we proposed an efficient patch validation mechanism by clustering patches into equivalence classes according to the *effect* they have on the symbolic heap. The effect-analysis on patches can be potentially extended to other use cases in the future, such as learning the effects of existing error handling routines in the program.

8 Data Availability

The artifact accompanying this paper is available from https://doi.org/10.5281/zenodo.8389675. For the latest version of EffFix, we have open-sourced it at https://github.com/nus-apr/EffFix.

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