Validation of Automatically Generated Patches
AN APPETIZER

Ali Ghanbari
University of Texas at Dallas, TX 75080, USA
ali.ghanbari@utdallas.edu

Abstract—In the context of test case based automated program repair (APR), the research community call the patches that pass all the test cases but fail to actually fix the bug test case overfitted patches. Currently, overfitted patches has to be manually inspected by the users. Being a labor intensive activity that hinders widespread adoption of APR tools, automatic validation of APR-generated patches has been the topic of research in recent years. In this paper, we point out the limitations of the existing techniques/methodologies that call for further research, and introduce two promising directions toward effective automatic patch validation: (1) motivated by the relative effectiveness of anti-patterns, we propose to use statistical techniques to avoid the uncomputability of applying some of the anti-pattern rules and automate the technique. Our results show that we achieve at least 57% precision. (2) We present a proposal for a semi-automatic technique that helps the programmers in finding properties of the patched methods and stress testing the patches based on those properties so as to filter out overfitted ones as many as possible.

I. INTRODUCTION

Manually debugging a defective program is notoriously difficult and costly. Automated program repair (APR) \([1]\) aims to fix the bugs with minimal human intervention, thereby reducing debugging costs. Based on the steps taken for fixing a bug, APR techniques can be divided into two broad categories: (1) techniques that monitor the execution of the subject program to find deviations from given specifications, and heal the program by modifying its run-time state in case of any abnormal behavior \([2]\); (2) generate-and-validate techniques that modify program text based on certain rules, and then use either tests or code contracts as the oracle to validate each generated candidate patch for finding plausible patches (i.e., the patches that can pass all the tests/checks), that are further checked to find correct patches (i.e., the patches that genuinely fix the bug) \([3]–[17]\).

Although promising steps toward applying APR in the industrial projects have been taken \([18], [19]\), state-of-the-art APR techniques suffer from three main shortcomings: scalability, applicability, and accurate patch validation \([20]\). Scalability refers to the ability of an APR technique in handling large, real-world programs. Applicability is the ability of the technique in handling different programming idioms, languages, or even different programming paradigms. Finally, patch validation refers to the process of classifying the patches generated by the APR tool into genuine and plausible patches.

In a real-world situation, programs often lack formal specifications, so generate-and-validate APR techniques usually use existing test cases to validate generated patches. But since test cases only partially specify the behavior of the programs, many of the generated patches happen to pass all of the test cases without actually fixing the bug. This makes APR techniques produce many plausible but incorrect patches, aka test case overfitted patches \([21]\) (or simply overfitted patches). The process of validating APR-generated patches has to be manual for the oracle problem is undecidable \([22]\), but manually analyzing each and every one of the plausible patches could be as costly as directly going about fixing the bug \([23]\). Thus, a convenient method for post-processing the automatically generated patches before reporting them to the developers is a need. This need is particularly pronounced in the case of APR techniques (e.g. \([24]\)) that are able to explore large search spaces and finding genuine patches that are ranked after tens of incorrect patches.

Recently, a spectrum of techniques for the identification of test case overfitted patches, ranging from manual to fully automatic, has been proposed. In the side figure, we have depicted the level of automation that each of the techniques offer. On the one side of the spectrum, we have manual inspection. DifTGen \([25]\) is one of the first attempts toward automating patch validation that relies on the human developer to reason about the quality of an execution due to a given patch. Anti-patterns \([26]\) is a set of heuristics that judge correctness of patches based on the kind of transformations conducted by an APR tool. Except for a couple of undecidable checks in the set (e.g., deciding whether or not a Boolean expression is a tautology), applying anti-patterns can be fully automated. On the other side of the spectrum, we have fully automatic techniques: Opad \([27]\) is a fuzzing-based tool that proves effective in case of programs written in C-like programming languages; UnsatGuided \([21]\) is based on the idea of automatically generating test cases so as to strengthen repair constraints that are used in semantic-based APR techniques such as NOPOL; lastly, similarity-based heuristics \([28]\) make judgments about correctness of the patches based on the similarity of execution of test cases on the original and patched versions of the target program.

Following \([21]\), we classify test case overfitted patches into three kinds: (1) patches that fully fix the bug but introduce regression (i.e., break the desired functionality); (2) patches that partially fix the bug but does not break the intended
functionality; (3) patches that partially fix the bug and also introduce regression. Such a classification of overfitted patches makes it easier for us to reason about the limits of patch validation techniques. In particular, techniques that are intended to generate regression test cases (e.g., DiffTGen, Opad, and UnsatGuided) are unlikely to be able to address cases (2) and (3). To the best of our knowledge, the work on similarity-based automatic patch validation \([28]\) is the first attempt toward identification of patches that belong to classes (2) and (3).

In this paper, we present a brief literature review of state-of-art patch validation techniques while emphasizing on the limitations of the techniques in identifying incorrect patches according to the aforementioned classification of overfitted patches. We argue that although the heuristics presented in ICSE’18 paper \([28]\) seem promising, more work needs to be done so as to draw any reliable conclusion about the effectiveness of similarity-based patch validation. Specifically, a closer examination of the patches that the technique had successfully classified reveals that most of the patches happen to affect the same method or even share the same line. Based on the discussion in §III-D, this might pose a serious threat to the external validity of such a fully automatic technique.

We also show that anti-patterns is among the most promising approaches for automatic patch validation in managed programming languages. However, the technique, as it is \([26]\), suffers from a couple of problems: (1) since some of the anti-patterns rules depend on certain conditions that are in general impossible to decide (e.g., whether or not a Boolean expression is a tautology or an expression in the body of a loop is a variant), automatically applying such rules is theoretically infeasible; (2) the rules are not precise enough and fail to admit 9% of the genuine patches in our study. We propose to use machine learning techniques to avoid uncomputability problem of applying anti-pattern rules. We attempt to avoid imprecision in anti-patterns by taking contextual information into account. Our current results show that we can achieve 57% precision, but we are positive that we can improve this precision significantly further. We believe this work is a promising starting point for efficient, effective fully automatic patch validation techniques. We envision a future work where we mine hundreds of thousands of human-written patches obtained from GitHub and use even more precise deep neural network models to classify patches.

Furthermore, we give a proposal for automating property-based testing for patch validation. We hypothesize that helping the programmers in providing properties (e.g., metamorphic relations \([29]\)) can supply the patch validation techniques with a reliable source of information about the intended behavior of the program, while avoiding overwhelming the programmers with low-level details of program executions (e.g., reporting concrete values of program variables and the obligation of interpreting those values in DiffTGen). We believe that this is a sweet spot between manual and fully automatic approach to patch validation, and could provide guidelines for practical patch validation and help adoption of test case based APR tools in industrial settings.

In summary, the paper makes the following contributions:

- **Study**: we present a study and literature review emphasizing on the limitations of state-of-the-art patch validation techniques. We hope our results and comments will be considered constructive by the research community and motivate more work in the area of automated validation of APR-generated patches.

- **Automation**: we show that using machine learning techniques we can automate anti-patterns, one of the most promising techniques so far, and avoid its uncomputability problems. Our current results show that we can achieve 57% precision. We believe this work is an encouraging starting point for fully automatic patch validation techniques that use hundreds of thousands of data points to build more effective, precise models.

- **Guidelines**: we propose a property-based technique for patch validation that we believe is a sweet spot between manual and fully automatic approach to patch validation, and provides guidelines for practical patch validation and help adoption of APR tools in industrial settings.

In what follows, we review the basic concepts that we have used in the rest of the paper (§II). We present a literature review of state-of-the-art patch validation techniques in §III. Next we introduce our work on automating anti-patterns and the proposal for semi-automatic patch validation (§IV). We conclude the paper with a discussion on the future work (§V).

II. BACKGROUND

A. Program Invariants and Loop Variants

An invariant is a logical assertion on the state of a program that always holds during a certain phase of the execution of the program \([30]\). For example, a loop invariant is a condition that is true at the beginning and end of every iteration of a loop. Having invariants is essential for proving program properties \([31]\), \([32]\), but it can also be used for program understanding, test case generation, and many other applications.

Writing invariants (esp., inventing workable loop invariants) is notoriously difficult and its automation is theoretically impossible \([30]\). Thus, researcher have sought heuristic solutions for inferring (likely) invariants, either statically \([33]\), \([34]\) or dynamically \([35]\). The techniques are best efforts for inferring program invariants and do not always succeed in inferring correct and/or complete invariants. The logical formulae proposed by these techniques can be thought of as potential program invariants at certain points, hence the name likely program invariants.

Daikon \([35]\) is a general-purpose dynamic invariant inference system that is able to infer likely class invariants, as well as invariants at the method entries/exists (aka method contracts). Daikon is working by observing program executions under a set of test cases and matching the executions with a set of predefined program invariant templates and then reporting those that are most likely to be true in subsequent executions. Daikon is a highly extensible and robust invariant inference system that has been successfully used in solving...
real-world problems [36]. In this work, we are going to use (an extended version of) Daikon to infer likely properties (e.g., metamorphic relations) for presenting to the user for approval and/or improvements.

A similar notion is the concept of loop variants. A loop variant for a loop is referred to a function mapping program variables to a value that is monotonically decreasing in each iteration of the loop. Similar to program invariants, inferring precise loop variants in an automatic fashion is infeasible.

B. Property-based Testing

Due to the undecidability of test oracle problem [22], it is impossible to automatically generate test cases. Property-based testing [57] is based on the idea of automatically generating test cases when a formal specification of the system under test, as a relation over its inputs and output (aka properties), is given. The basic idea is to randomly generate test inputs to find the cases that are qualified as valid inputs while make the program produce outputs that are not valid based on the given specification. QuickCheck [38] is a property-based random test generation tool for Haskell [39] and with several incarnations for other languages such as Java [40] which is able to generate hundreds of test cases within a few seconds.

Unfortunately, because of the complexities of the real-world systems, it is almost always impractical to capture the behavior of the system as a relation over its inputs and outputs. Metamorphic testing [29] alleviates this problem by reasoning about the relations between outputs of a system, rather than fully formalizing its input-output behaviour. These relations are often referred to as metamorphic relations [41], that are instances of program invariants. For example, consider testing a program that computes sin function. Instead of checking the output of the program for each randomly generated test input, we could rely of the metamorphic relation $\sin(x) = \sin(\pi-x)$ to check the correctness.

Our experiments show that Daikon is able to infer properties about the system under test and it also gives useful hints for developing metamorphic relations.

C. Software Agitation

Software agitation [36] combines the results of research in test-input generation [42], [43] and dynamic invariant detection [15]. Roughly speaking, software agitation comprises two main steps: (1) test input generation and invoking the methods of the system under test using the generated inputs; (2) examining execution traces of the system under test when applying the program on the generated inputs to infer assertions about the behavior. The assertions are in form of relationships between various values of the source code variables that were determined to hold under a variety of different inputs—e.g., for a method $\max$ computing the maximum of two integers $a$ and $b$, agitation might infer that $\max(a, b) \geq a \land \max(a, b) \geq b$.

In Section IV we use a variant of software agitation to dynamically infer likely invariants (some of which might be useful properties or metamorphic relations or give hints on the development of such relations) that subsequently presented to the user for approval and/or improvement.

III. STATE OF THE ART

In this section, we present a brief review of state-of-the-art patch validation techniques. The goal is to emphasize on limitations of the current work and motivate future research.

A. Anti-patterns

Anti-patterns, as revisited in [26], refers to prohibited program transformations named after recurring wrong design decisions in software architecture [44]. The hypothesis is that there should be a set of generic program transformations that APR techniques commit that lead to plausible but incorrect patches. In their paper [26], Tan et al. manually analyze the fix results of two APR techniques GenProg [4] and SPR [2] on GenProg [45] and CoREBenchmark [46] benchmark programs so as to identify program transformations that lead to plausible but incorrect patches. These transformations are called anti-patterns to stress that these are the ones that should be avoided. The paper identifies a set of 7 anti-patterns and claim that they are generic and language, bug, and APR technique agnostic. Among these 7 anti-patterns, 5 are prohibiting deletion of statements, 1 is prohibiting “early exits,” and 1 is intended to prohibit insertion of tautologies. The promise of anti-patterns is that by prohibiting transformations that are not recommended, the search space of a given APR technique will be reduced. This means that the likelihood of finding a genuine patch (provided that it exists in the search space) will also increase, or at least the number of plausible but incorrect patches will be decreased. The paper attribute this to the fact that anti-patterns avoid program transformations that are likely to trivially pass the given test cases, e.g. by admitting patches that remove less functionality. Furthermore, the paper empirically demonstrates that anti-patterns, by reducing the search space to be explored, can speed up repair process by at least 1.5X.

As we have just mentioned, anti-patterns can be used to improve the performance of APR tools, but in this paper we are focusing on its ability in filtering out incorrect patches. Anti-patterns are heuristics that require minimal human intervention. In fact, by setting aside the anti-pattern prohibiting insertion of tautologies and deletion of loop variants (which are undecidable in general) the technique can be fully automated. Thus, we place this technique toward the right end of our spectrum of techniques, next to fully automatic patch validation techniques. Although we believe anti-patterns is one of the most efficient, effective automatic techniques, the current form of anti-patterns suffers from imprecision problem as it dismisses genuine fixes. In our experiments, independent of the APR technique, or patch ranking strategy, applied anti-patterns always dismissed a number of genuine patches.

Fig. 1 summarizes the results of our experiments on applying anti-patterns on three recent APR tools, namely PraPR [24], SimFix [47], and CapGen [8]. PraPR is a fast mutation-based generate and validated APR technique that operates at the level of JVM bytecode, SimFix is a recent APR tool that fixes the programs by using similar code snippets in the buggy code base, and CapGen is an APR tool which can be
thought of as the infamous GenProg [4] that manipulates more fine-grained program elements (expressions vs. statements) and that leverages some form of contextual information to avoid nonsensical patches. We choose these tools for two reasons: (1) they do not stop after finding a test adequate patch (we modified SimFix to be so); (2) their implementation is relatively robust and are applicable to all the 395 bugs from Defects4J v1.2.0 [48] (including Mockito and Closure).

The process of our experiment is as follows. We applied the tools on all the 395 bugs in Defects4J v1.2.0 with a 5-hour time limit (no time-out occurred). We ran PraPR under two configurations; one uses only Ochiai [19] suspiciousness values of the patched locations to rank the patches, and the other breaks the ties of Ochiai-based ranking using mutation-operator scores mined from HD-Repair [50] data set (denoted PraPR+ in Fig. 1). Upon completion of the repair process, we examined the patch reports and filtered out transformations that correspond to either of the 7 anti-patterns. According to Fig. 1, anti-patterns by removing plausible but incorrect patches, helped PraPR (PraPR+) to rank 27.8% (resp., 8.3%) more correct patches within Top-1, but at the same time in total it misses up to 9.3% (resp., 9.3%) of the correct patches. As per the charts, however, in case of SimFix and CapGen anti-patterns have only destructive effects and misses 3 and 1 correct patches, respectively. These observations suggest that anti-patterns tend to have some destructive effects. In case of PraPR, this destructive effect gets more pronounced once the tool manages to rank more correct patches at Top-1 (note that PraPR+ improved by only 8.3%). We attribute this deficiency of anti-patterns to the fact that the rules are not fine-grained enough and many unrelated patches match the same rule.

Despite its shortcomings, we acknowledge that so far anti-patterns are the most effective and efficient method for getting rid of plausible but incorrect patches. Specifically, unlike similarity-based technique [28] which runs out of tens of gigabytes of RAM and take several minutes to finish, applying anti-patterns is a quite lightweight process; basically it is just a string matching, provided that we exclude the anti-patterns prohibiting insertion of tautologies or deletion of loop variants.

Motivated by the relative effectiveness of anti-patterns and the deficiencies of the current form of this technique, we have re-implemented this idea while having two main goals in our mind: (1) avoid undecidable checks by using machine learning techniques and automate the process of applying anti-patterns; (2) use a much larger data set of patches so as to provide a set of more fine-grained rules while supplying each anti-pattern with some contextual information, as mere transformations convey meager information about their effects. In §IV-A we describe details of this research activity.

B. Patch Validation through Regression Test Generation

In [25], Xin and Reiss, introduce a technique that identifies the patches that break the subject program (i.e. those patches that introduce regression). The technique has been implemented as a tool named DiffTGen. The technique identifies overfitted patches through observing semantic differences between the original buggy program and the patched program. In order to work, DiffTGen needs the following ingredients: (1) a buggy program $P_b$; (2) a patched program $P_p$ (which is produced using an APR technique); (3) an oracle which can decide correct behavior. The workflow of DiffTGen is as follows. First, DiffTGen computes the diff $\delta$ between $P_b$ and $P_p$ to generate a so-called test target $P_t$ by applying $\delta$ on $P_b$. Next, DiffTGen instruments $P_b$ and $P_p$. Instrumentation is done in order to make $P_b$ and $P_p$ to print out the details of their computation. The tool then applies a test generation tool (Evosuite [42], in this case) to generate test inputs revealing semantic differences between the buggy and patched versions. However, generating arbitrary inputs might not lead to revealing the semantic differences. Thus, the tool creates so-called coverage goals by generating a dummy statement (a statement without any computation effect serving just for coverage purposes) before the location of the patch so as to guide the test input generator in such a way that they generate inputs that make the output of the two programs differ. For example, suppose that the patch is to modify the condition of an existing if-statement, then the dummy statement will be an if-statement such that generating an input to cover its then-branch amounts to covering the then-branch in the buggy program and else-branch in the patched program, or the other way around. After generating the inputs, the tool runs instrumented buggy and patched programs to observe their behavior. In case of seeing any difference, the tool consults the difference with the oracle (which is intended to be a human-being [25], [51], but in this research an instrumented version of programmer-patched program is used as oracle). The oracle in turn decides if the behavior of the patched program is desired, and (if possible) specifies the expected behavior (e.g. by producing the expected value of a function output). By having this judgment and the expected output, DiffTGen is able to generate a test case that passes on the buggy program but fails on the patched program, thereby revealing the regression.

![Fig. 1. The effect of anti-patterns on the patch ranking of three state-of-the-art APR tools. Each chart shows the number of correct patches ranked at Top-1, Top-10, and All positions, before and after applying anti-patterns.](image-url)
C. Fuzzing-based Patch Validation

In [27], Yang et al. introduce Opad to automatically filter out overfitted patches in APR techniques. Similar to the previous techniques, [21], [25], Opad is only able to detect regression introducing overfitted patches. The technique identifies overfitted patches through generating new test cases using fuzzing [54] and a so-called O-measure (Overfiteness measure) metric. Opad uses an off-the-shelf fuzzer (AFL [55], in this case) with two class of predetermined oracles, i.e., memory safety and crashes. Crash can be seen as any abnormal termination of the program. Memory safety issues studied in [27] include buffer overflows, use of uninitialized variables, and memory leaks. Opad uses AFL to generate test inputs that exercise the patches generated by an APR technique and observes if the execution shows any of the aforementioned issues via O-measure value computed for the execution.

The paper presents a formal characterization of O-measure and argues that calculating the ideal value of O-measure is theoretically impossible. The paper, however, proposes a way to approximate the value of O-measure such that its value indicates “how worse the patched program performs compared to the original program.” The approximation is done as follows. If the patched program manifests more memory safety issues (e.g. more bytes of memory leaked), the value of O-measure gets incremented by one. At the end, all patches with non-zero values of O-measure are reported as overfitted.

The paper reports the use of Opad in the context of GenProg [3], AE [56], SPR [9], and Kali [57] on 45 bugs that formerly used to evaluate GenProg and SPR. The experimental results show that, surprisingly, even fuzz testing with only two simple, hard-coded oracles can filter out over 75.2% of the overfitted patches. This achievement is impressive, but we believe that the technique is rather limited due to the following reasons: (1) fuzz testing is not guaranteed to perform well; (2) the oracles used in the paper are specific to C programming language (and languages in this family, such as C++), and the memory safety issues are almost completely eradicated in garbage-collected languages like Java (this is while the oracle related to memory safety has an important contribution in the success of Opad [27]). It is worth noting that another study [28] shows that Opad does not perform satisfactorily for Java-based patches.

Recently Gao et al. introduce Fix2Fit [58], a tool that integrates generation, detection and discarding of crashing patches. The technique filters out overfitted patches by distinguishing candidate patches in terms of behavior. New test cases are generated based on a grey-box fuzzing strategy, and crash-freedom is used as the oracle to discard plausible fixes that crash on the new tests. Despite showing promising results for C programs, fuzzing is still less effective in the context of managed, type-safe programming languages like Java.

D. Similarity-based Patch Validation

In their ICSE’18 paper [28], Xiong et al. propose two heuristics, namely PATCH-SIM and TEST-SIM, for automatic patch classification. Intuitively, PATCH-SIM is based on the hypothesis that a correctly patched program behaves similar to the original program on originally passing test cases (i.e. the patch does not introduce regression), while it behaves differently on originally failing test cases (i.e. it fixes the bug “as much as possible”). TEST-SIM is another heuristic that is used to approximate an ideal test oracle. Roughly speaking, any two test cases with similar executions are likely to produce the same results while two tests with different executions are likely to produce different results. This allows us to generate new test cases to make our original test suite stronger, thereby making better use of the first heuristic. In this section, we will have a closer look at the data set used to evaluate effectiveness of the two heuristics. Backed by our study, we claim that the idea of using PATCH-SIM and TEST-SIM to validate overfitted patches is a promising direction, but a more comprehensive experimentation is needed to draw a reliable conclusion.

The paper uses 139 patches generated by four APR techniques (i.e., jGepProg [59], jKali [59], HD-Repair, ACS [60], and NOPOL [61]) as the data set of patches to show effectiveness of PATCH-SIM and TEST-SIM. The data set of patches is available online [62]. We manually inspected each of the patches in the data set, and realized that it contains 11 pairs of duplicated patches, 34 patches that target only 16 different lines, and 30 patches that target only 12 different methods. Even if we set the duplicated patches aside, the use of Longest Common Subsequence (LCS) [63] to judge similarity of execution traces, when 46% of the patches in the set target either the same line or the same method, poses a serious threat to the validity of the claims made in the paper regarding the effectiveness of the heuristics. Roughly speaking, assume patches $p_1$ and $p_2$ target the same line of the same bug. In this case, for each test case, every execution trace corresponding to $p_1$ shares a (identical) prefix with every execution trace corresponding to $p_2$. Thus, if we use LCS to judge the similarity of execution traces, we might
give $p_1$ and $p_2$ the same label (either both correct or both incorrect), and this happens to help filtering out all plausible but incorrect patches in the data set used in the study. To confirm this, we attempted to reproduce the experiments under two configurations: (1) using LCS (original configuration); (2) using Levenshtein distance \cite{64} to compute similarity of execution traces. All our experimentation is done on a Dell workstation with Intel Xeon E5-2660 v4 @ 2.00GHz and 225GB RAM, running Ubuntu 14.04.6 LTS and Oracle Java 64-Bit Server version 1.7_0_80.

Tables \ref{table1} \ref{table2} \ref{table3} and \ref{table4} summarize our results. Table \ref{table1} lists duplicated pairs of patches, Table \ref{table1} groups all the patches that target the same line, and Table \ref{table3} groups all the patches that target the same method. Columns “Patch Id” and “User Annot.” in each table present the ID and ground-truth label for each patch. The columns “LCS” and “Leven.” present labels for each patch when using the original LCS and Levenshtein distance, resp., for computing patch similarity. In the tables, “I” represents a plausible but incorrect patch, “C” indicates a correct (genuine) patch, and “NA” represents lack of information due to failure of the prototype (e.g., by running out of heap space) and/or the off-the-shelf components that it depends upon (e.g., Randoop \cite{43}). Highlighted rows represent failures that are confirmed by the authors of \cite{28}, while other cases are attributed to differences in hardware and/or OS setup.

According to the data presented in the tables, we get 2.7% improvement in the number of correctly classified patches when we use Levenshtein distance for measuring similarity of execution traces. Therefore, we believe despite poor benchmark data selection in \cite{28}, the use of PATCH-SIM and TEST-SIM heuristics to validate overfitted patches is still a promising direction and deserves further research.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Patch Id & User Annot. & LCS & Leven. \\
\hline
65 & I & I & I \\
66 & I & I & I \\
82 & I & C & I \\
83 & I & C & I \\
99 & I & I & I \\
90 & I & I & I \\
181 & I & I & I \\
185 & I & I & I \\
77 & I & I & I \\
92 & I & I & I \\
23 & I & I & C \\
151 & I & I & C \\
51 & I & C & I \\
53 & I & C & I \\
55 & I & I & I \\
170 & I & I & I \\
1 & I & I & I \\
2 & I & I & I \\
30 & I & NA & NA \\
31 & I & NA & NA \\
44 & C & C & I \\
45 & C & C & I \\
\hline
\end{tabular}
\caption{Pairs of duplicate patches in the data set of \cite{28}}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Patch Id & User Annot. & LCS & Leven. \\
\hline
24 & I & C & I \\
152 & I & C & I \\
6 & I & C & I \\
7 & C & C & I \\
75 & I & C & C \\
76 & I & C & C \\
36 & I & I & C \\
159 & I & I & C \\
74 & I & I & I \\
174 & I & I & I \\
204 & C & C & I \\
HDR9 & I & C & I \\
14 & I & C & I \\
91 & I & I & I \\
47 & HDR6 & C & C & I \\
68 & I & I & I \\
69 & I & I & I \\
79 & I & I & C \\
177 & I & C & C \\
11 & I & C & C \\
89 & I & C & C \\
29 & C & NA & NA \\
196 & C & NA & NA \\
38 & I & I & I \\
161 & I & C & I \\
187 & I & NA & NA \\
HDR10 & I & NA & NA \\
21 & C & C & I \\
150 & I & I & I \\
73 & I & C & I \\
175 & I & C & I \\
27 & I & NA & NA \\
154 & I & NA & NA \\
\hline
\end{tabular}
\caption{Groups of patches in the data set of \cite{28} targeting the same line.}
\end{table}

\section{E. UnsatGuided Patch Validation}

In \cite{21}, Yu et al. propose an approach, named UnsatGuided test case generation, to mitigate overfitting problem in synthesis-based APR techniques, specifically NOPOL. The basic idea is to discard those generated test cases that contradict the patch constraint that is already obtained from programmer-written passing test cases. If the generated test case does not contradict the existing patch constraint, the set of regression test cases will be augmented with this newly created test case thereby leading to a stronger patch constraint. This, in turn, increases the likelihood of producing patches that does not introduce regression. Targeting patch constraint in order to increase the quality of the resulting patches is consistent with the findings reported in \cite{65}. The paper makes several important observations/conclusions, including but not limited to the following: (1) regression-introducing patches are as frequent as incomplete fixes; (2) UnsatGuided approach can effectively reduce the number of regression-introducing patches, while it has minimal effect on incomplete fixes; (3) UnsatGuided approach does not break any already correct fix, however it can turn an overfitting patch into a correct one. The limitation observed in (2) suggests that UnsatGuided approach is only able to filter out regression-introducing patches and it is unable to deal with partial fixes.
IV. TOWARD AUTOMATING PATCH VALIDATION

In this section, we give the details of our implementation of anti-patterns and present our experimental results. We then introduce our proposal for semi-automatic patch validation.

A. Automating Anti-patterns

1) Data Set of Patches: As we mentioned earlier, our implementation of anti-patterns is intended to take contextual information into account along with the actual transformations. Also, we base our implementation on a much larger data set. Since we are to automate anti-patterns without exposing the details about each rule to the users, we do not need to worry about understandability of our rules. Thus, in order to make the implementation even faster and readily applicable to a wider range of APR techniques, we make our anti-patterns work at the level of JVM bytecode instructions, we end up with 55 abstract patterns and code clone detection [69]. Following the work on bytecode level code clone detection [69], we abstract away the unnecessary details encoded within each JVM bytecode. For example, the type information about the values of the variables being accessed, or the values of the constants pushed into the bytecode are abstracted away.

We have collected our data points among those produced by PraPR, SimFix, and CapGen on 587 bugs from Defects4J v1.4.0 [67] (we excluded the bugs for Guava and Gson projects due to build and/or test incompatibility issues.) By applying the tools on the bugs, we collected 2,403 patches generated by PraPR, 56 generated by SimFix, and 3,764 patches generated by CapGen. Among these patches 90 are identified to be correct while the rest are labelled as incorrect.

When we are manually applying the original rules of anti-patterns [68], we attempt to match the body of a given anti-pattern rule with the transformed code snippet so as to decide whether or not the rule is applicable. This suggests that there is a similarity between the process of applying anti-patterns and code clone detection [69]. Following the work on bytecode level code clone detection [70], we abstract away the unnecessary details encoded within each JVM bytecode. For example, the type information about the values of the variables being accessed, or the values of the constants pushed into the stack, are inconsequential when it comes to reasoning about semantic similarity. By abstracting the unnecessary details of JVM bytecode instructions, we end up with 55 abstract

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| Patch Id | User Annot. | LCS | Leven. |
|----------|-------------|-----|--------|
| 62       | I           | C   | I      |
| 63       | I           | C   | I      |
| 64       | I           | C   | I      |
| 173      | I           | C   | I      |
| 202      | I           | C   | I      |
| 18       | I           | NA  | NA     |
| 93       | I           | NA  | NA     |
| 193      | I           | NA  | NA     |
| 20       | I           | NA  | NA     |
| 32       | I           | NA  | NA     |
| 33       | I           | NA  | NA     |
| 158      | I           | I   | C      |
| 198      | I           | I   | C      |
| 58       | I           | I   | I      |
| 171      | I           | C   | I      |
| 54       | C           | C   | I      |
| 201      | I           | C   | I      |
| 59       | I           | C   | I      |
| 172      | I           | C   | I      |
| HDR5     | I           | C   | I      |
| 166      | I           | C   | I      |
| 26       | C           | C   | I      |
| 153      | I           | C   | I      |
| 77       | I           | I   | C      |
| 208      | I           | I   | C      |
| 48       | I           | I   | I      |
| 167      | I           | I   | I      |
| 203      | C           | C   | I      |
| HDR8     | I           | I   | I      |

Σ = 30
Σ C = 4
Σ C = 15
Σ NA = 6

TABLE III

GROUPS OF PATCHES IN THE DATA SET OF [23] TARGETING THE SAME METHODS

| Patch Id | User Annot. | LCS | Leven. |
|----------|-------------|-----|--------|
| 4        | I           | I   | I      |
| 5        | I           | C   | I      |
| 8        | I           | I   | I      |
| 9        | I           | I   | I      |
| 10       | I           | C   | C      |
| 12       | I           | C   | I      |
| 13       | I           | I   | I      |
| 189      | C           | NA  | NA     |
| 15       | I           | I   | I      |
| 16       | I           | I   | I      |
| 19       | I           | I   | I      |
| 188      | C           | NA  | NA     |
| 191      | C           | C   | C      |
| HDR1     | I           | C   | I      |
| 28       | I           | NA  | NA     |
| 194      | C           | NA  | NA     |
| 155      | I           | NA  | NA     |
| 195      | C           | NA  | NA     |
| HDR3     | I           | NA  | NA     |
| 157      | I           | NA  | NA     |
| 197      | C           | NA  | NA     |
| 34       | I           | I   | C      |
| HDR4     | I           | C   | C      |
| 199      | C           | NA  | NA     |
| 160      | I           | I   | C      |
| 37       | I           | C   | I      |
| 162      | I           | C   | I      |
| 163      | I           | C   | I      |
| 165      | I           | C   | C      |
| 49       | I           | C   | C      |
| 168      | I           | C   | I      |
| 169      | I           | I   | I      |
| 53       | I           | I   | I      |
| 67       | I           | I   | I      |
| 74       | I           | I   | I      |
| 176      | I           | I   | I      |
| 205      | C           | C   | I      |
| 206      | C           | C   | I      |
| 207      | C           | C   | C      |
| 209      | C           | NA  | NA     |
| 78       | I           | C   | C      |
| 80       | I           | I   | C      |
| 81       | I           | I   | C      |
| 180      | I           | C   | I      |
| 84       | I           | I   | I      |
| 182      | I           | C   | I      |
| 183      | I           | I   | I      |
| 184      | I           | I   | I      |
| 210      | C           | C   | I      |
| 186      | I           | I   | I      |

Σ = 53
Σ I = 39
Σ I = 22
Σ I = 30
Σ C = 14
Σ C = 19
Σ C = 11
Σ NA = 12
Σ NA = 12

TABLE IV

ALL THE REMAINING PATCHES IN THE DATA SET OF [23] THAT TARGET DIFFERENT LOCATIONS
instruction. At the bytecode level, in order to incorporate contextual information along with our rules for anti-patterns, we take a window of fixed size around the location of the patch. We do word embedding by mapping these abstract instructions into integers 0 through 54. In this way, we can map each window of instructions into an integer vector. Fig. 2 illustrates this process for a small window size. For each pair of buggy-fixed version of the program, we obtain a pair of integer vectors. We use this information, together with ground truth label for the patch (which is either CORRECT or INCORRECT) and the identifier for the transformation operator, to train several different models that are described in the following section.

2) Method: We used six different models in our experiments: (1) multinomial hidden Markov model (SeqLearn, no labels); (2) logistic regression (TF-IDF, PCA, feature union); (3) Pytorch LSTM networks (skorch, padding with sequences vs. deindexing and dicts); (4) decision tree (TF-IDF vs. CountVectorizer); (5) support vector classifier; (6) naive Bayes. On the initial run, the data set is constructed with different bytecode window sizes around the patch location. The window sizes are used as hyperparameters. Each potential model is specified in a pipeline. Sklearn has support for constructing a hyperparameter grid for nested models and models nested within pipelines via a dunder syntax. This is used to search hyperparameter grids for each of the models in the suite with 10-fold cross-validation. Since hyperparameter optimization on PyTorch was not as well supported as we were expecting, we used a library by the name of Skorch, which is quite promising.

Our data set contains several thousands of data points with label INCORRECT while only 90 instances with label CORRECT. We did random oversampling to deal with this unbalanced data set. We leave using human-written patches scraped from GitHub as a future work. Some of the preprocessing is made easier by the type of data. The bytecode sequences are very similar to text, with a relatively small vocabulary size. For example, with OneHot encoding, the preprocessor and tokenizer are both replaced with identity functions. On the relevant torch models, no preprocessing of the sequences are conducted before passing to the torch embedding layer. It would be nice to reduce the dimensionality of the OneHot encoding, because the embedding layer still has the parameter overhead of a fully connected layer. Unfortunately, PCA is lossy, and we cannot afford to reduce the efficiency of the data that we currently have. In a future work, we plan to address the efficiency of our data set.

Fig. 3 summarizes our results. The decision tree has the best accuracy, but it classifies every example as INCORRECT, so it has very poor performance on precision, recall, and F1. The logistic regression model with TF-IDF, and a feature union with the OneHot encoding of the operator used, is arguably the most useful model. It has the best precision and F1 scores, and the second best accuracy. The model uses the buggy byte sequence with a window size of 21 bytecodes. It is worth noting that this window is large enough to hold enough information about the context within which the transformation is happening.

B. Proposal

Fig. 4 illustrates an architectural overview of the proposed system for semi-automatic patch validation. Roughly speaking, having a buggy program \( P_b \) and a patched program \( P_p \), the workflow is as follows. We use a random test generation tool (Randoop [4] in this case) to generate a bunch of test inputs for the target method in \( P_b \). We instrument the target method (and all of its immediate callers) so as to retrieve complete path spectrum \( [71] \) (CPS), before running the target method with the generated test inputs and original test cases. After running all the tests we get a set of CPS—i.e. a set of sequences of executed statements. We compute the distances between the sequences corresponding to the generated test inputs and the sequences corresponding the the original test cases. We heuristically label those generated test cases that are most similar to the originally passing test cases as passing. In this way, we obtain a larger, richer set of passing test cases. Next, we pass the buggy program \( P_b \) and the set of passing test cases to a dynamic invariant inference system (Daikon [35] in this case) so as to infer invariants for the target method. We then do a light-weight post-processing on the produced logical assertions before presenting them to the user for approval and/or improvement. Once the user submits the finalized set of invariants to the system, it annotates the target method in the patched program \( P_p \) accordingly. We then pass the annotated program to a property-based testing system (junit-quickcheck [40] in this case). We repeat this process for each buggy and patched version corresponding to each plausible patch. Finally, we sort the plausible patches, in ascending order, based on the number of failures they induce before presenting the list of patches to the user. In what follows, we describe each of the components of the system in more detail.

1) Generating extra passing test input: Inspired by the idea of software agitation, introduced in §II-C we exercise the program with many test inputs so as to gain insights about the behavior of the target method in the buggy program. However, unlike software agitation, we confine ourselves to passing test cases for passing test cases describe the desired behavior of the target program and are suitable for inferring properties (such as metamorphic relations).

Since we are using Daikon for inferring invariants, we need to provide an enough number of test cases so as to generate statistically significant observations. To this end, we use Randoop to generate test inputs for the target method in the buggy program. We then instrument the target method (and all of its immediate callers) so as to retrieve CPS. We restrict instrumentation to the target method and its immediate callers so as to filter noises; the basic idea is that two tests may be different in statement executions outside the calling context of the target methods, but such a discrepancy is often not pertinent to the fault.

Once we instrument the buggy program, we execute all the test cases so as to obtain a set \( E = \{ \eta \mid \eta \text{ is a CPS} \} \) of
Fig. 2. A real world example of the abstraction process for the patch of the bug ChartJ from Defects4J. The top part of the figure illustrates the abstraction process for the buggy version, while the bottom part illustrate that of the patched version. From left to right, we compile the source code into bytecode (a simplified form of JVM bytecode is shown here), form a window around the patched location, and abstract the instructions before mapping the window of instructions into a vector of integers.

Fig. 3. Average accuracy, recall, precision, and F1 for different variants of the models that we experimented with.

execution sequences. This set is naturally partitioned into three subsets $E_p, E_f, E_g$ of execution sequences corresponding to the originally passing test cases, originally failing test cases, and generated test inputs, resp. Following [28], we use the distance between the execution sequences in $E_p$ and those in $E_p$ and $E_f$. We use normalized Longest Common Subsequence (LCS) distance: for each pair of execution sequences $\eta_1$ and $\eta_2$, we compute the distance as follows.

$$d(\eta_1, \eta_2) = 1 - \frac{\text{LCS}(\eta_1, \eta_2)}{\max(|\eta_1|, |\eta_2|)}.$$  

Finally, we keep those generated test inputs execution sequence of which is more similar to those of the originally passing test cases rather than those that correspond to originally failing test cases. More formally, assuming the function $e$ mapping a generated test input to its corresponding execution sequence in $E$, we use the following classification to keep those test inputs that are most likely to be passing test cases:

$$G = \{ t | t \text{ is a generated test input and } A_p(t) < A_f(t) \},$$ where $A_p, A_f$ are defined as follows

$$A_p(t) = \min \{ \{ d(\eta, e(t')) | \eta \in E_p \} \},$$

$$A_f(t) = \min \{ \{ d(\eta, e(t')) | \eta \in E_f \} \}.$$ 

The set $G$ augments the originally passing test cases, thereby providing enough information for the next step.

2) Inferring likely properties: We were unable to directly use Daikon system as it takes only a single execution trace into account when it infers the invariants. We have extended Daikon with an auxiliary subsystem which for each pair of execution traces recorded by Daikon, attempts to infer the following “templates” for properties that happens to be metamorphic relations:

- **R1**: checks if the output of a (non-void) method remains constant between any pair of executions.
- **R2**: checks if the output of a (non-void) method is multiplied by some constant when one of its parameters gets multiplied by a constant.
• **R3**: checks if the output of a method that returns a collection object (either an array or an instance of Collection) gets permuted between executions. We feed the extended Daikon with the augmented passing test cases and the buggy program so as to infer likely program invariants for the target method. Being based on the passing test cases, these invariants are most likely to specify the desired behavior of the system. We do a light-weight post-processing on the output of Daikon before presenting them to the user. In particular, Daikon generates many assertions about the fact that the type of certain fields do not change due to the execution of a method. These kind of assertions are unlikely to be as part of any useful property or metamorphic relations. Thus, we filter such assertions out. In summary, the post-processing is done as follows: (1) we conjoin class invariant to the pre- and post-condition inferred for the target method; (2) we filter out conjuncts that are most likely to be useless; (3) translate the remaining formula into an OCL-like \cite{72} formula before presenting the results to the user.

The resulting assertion is presented to the user for approval and/or rejection. Backed by our initial experiments with the implemented system, we believe that these invariants facilitate the development of useful properties or metamorphic relations by either generating them or providing hints for the user to write such properties.

3) **Property-based testing and ranking**: Once the user submits the finalized properties to the system, it annotates the target method in the patched program with the properties according to the submitted properties. We generate a property (marked with @Property annotation from junit-quickcheck) method whose parameters correspond to the parameters and the return value of the target method. We then use junit-quickcheck to do property-based testing, and record the number of failing test cases—those incorrect patches with fewer failures will be ranked first.

4) **Related work**: In the past few years a number of research papers have been published on the automatic inference of metamorphic relations. In \cite{73}, Su et al. present a technique, named Kabu, for inferring metamorphic relations to support differential testing. We could not reuse Kabu in that the tool is designed in such a way that it infers metamorphic relations from correct programs, while we want to infer such relations for a buggy program. Upulee and Bieman \cite{74}, as well as \cite{75}, \cite{76}, use machine learning techniques to predict likely metamorphic relations based on the control flow graph of the target methods. Similar to \cite{73}, these techniques also assume a correct program as input. In their paper \cite{77}, Troya et al. introduce a technique for automatically inferring likely metamorphic relations for model transformations with an assumption that the tester does not have any knowledge of the transformation.

V. **Conclusion and Future Work**

We presented a literature review of state-of-the-art patch validation techniques with an emphasis on their limitations. Specifically, we argued that although similarity-based patch validation \cite{28} is a promising research direction, a more comprehensive experimental study is needed so as to make more reliable judgments about its effectiveness. We also showed that anti-patterns, although efficient and relatively effective, has destructive effects in that it is imprecise and filters out correct patches. We proposed to use statistical techniques to avoid uncomputability problems with some of anti-patterns rules. Our experiments show that this is a promising direction for the construction of practical automated patch validation tools. Lastly, we presented a proposal for semi-automatic patch validation through automatic property-based testing. We involve human programmers in the process of patch validation, but unlike \cite{25}, \cite{51} we do not expose low-level details of the program state (i.e., concrete values of program variables) to the user. Instead, the user is asked to manipulate logical assertions and they are provided with either complete properties (e.g., metamorphic relations) or useful hints in developing such relations.

This work is a starting point for a couple of interesting research projects. We have obtained a data set of several thousands of correct patches from GitHub. We are implementing a more precise version of anti-patterns by trying different models, including deep neural networks. The current implementation of the proposed semi-automatic metamorphic testing is only applicable to programs with inputs and outputs whose types are restricted to: (1) primitive types; (2) String; (3) Collection of (1) or (2). We leave the task of handling methods with more complex types for future work.
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